OPTIMAL NETWORK AND MANAGEMENT OF ELECTRIC VEHICLE CHARGING STATIONS AT UNIVERSITY CAMPUSES

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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May 2019

ABSTRACT

Motivated by the necessity to reduce GHG emissions by commuting vehicles and improve users' convenience, this thesis is dedicated to proposing an optimal network and management of Electric Vehicle (EV) charging stations on campus making the most of the zero tailpipe emissions of EVs. The problem has been decomposed with identified critical components to construct a basic Mixed Integer Programming (MIP) model maximizing the convenience benefits and minimizing the construction costs. Moreover, an expanded model has been proposed in accordance with another sub-objective of gaining greater environmental benefits. Two models are solved by CPLEX in Python with necessary inputs from several sources. Last but not least, the validity of the models has been verified by linearized relaxation, sensitivity analysis, and scenario analysis, which prove the enormous applicability and capability of two models.

Keyword: Electric vehicle; Charging stations; Mixed Integer Programming; QGIS; CPLEX; Python; Google Maps API; Data analysis

BIOGRAPHICAL SKETCH

Xucheng Tang is a second-year Master of Science student in Civil Engineering with a concentration on Transportation Systems Engineering. In May 2019, he will finish his master study and graduate from Cornell University.

Xucheng graduated from Dalian University of Technology at Dalian, China in 2017. With the strong desire to continue his exploration in sustainable transportation at the undergraduate level, he decided to pursue his Master of Science degree in Transportation Systems Engineering at Cornell University.

During his substantial, exciting and unforgettable years at Cornell University, Xucheng consistently followed a systematic and multidisciplinary curriculum focusing on Data Science in Transportation and explored fields including, but not limited to, Transportation Systems Engineering, Data Science, Operation Research, Computer Science, and Finance.

Besides academics, Xucheng is an authentic empathic optimist in his life. Sports like Downhill Skiing, Archery, and Billiards enrich his days in Ithaca, NY, where Cornell University locates. He also enjoys communicating with people from diversified backgrounds and experiencing different cultures. Moreover, he sincerely appreciates everything he has encountered at Cornell and will bring it to further adventures in life.

This thesis is dedicated to my parents and girlfriend, who are supportive as always.

ACKNOWLEDGMENTS

Firstly, I would like to express my sincere gratitude to my master advisor Professor H. Oliver Gao. It is his extraordinary academic achievements across several fields, like transportation systems, environment, energy, and sustainable development, that inspire me to fearlessly explore unfamiliar academic areas. Professor Gao has always been supportive of me and my choice while also giving insightful advice whenever I need. Moreover, the original idea of my thesis is generated from one of his proposals. Many thanks! Professor Gao!

Besides, I would like to express my appreciation to the other member in my special committee – Professor Samitha Samaranayake. His excellent knowledge of optimization helps me to overcome several obstacles in this thesis from the very beginning. Furthermore, he is always willing to give guidance to me whenever I need. Thank you! Professor Samaranayake!

Also, I would like to thank Mr. Reed Huegerich, the Assistant Director of Cornell University Transportation and Delivery Services, who has helped me a lot on collection of raw data. Similarly, Mr. Keith Jenkins, the GIS & Geospatial Applications Librarian of Mann Library, offered me detailed guidance on QGIS. Thank you!

Then, I would like to thank all the instructors, students, alumni, and staff who I am lucky to work with in our Cornell Community. It is all of them together who make me believe the founding principle of Cornell University - *I would found an institution where any person can find instruction in any study.*

Finally, I would like to show my profound gratitude to my family for supporting me as always. My courage for life comes from their love.

Thank you all! All of your gifts will come with me to further adventures in the coming world of uncertainty.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Sustainability, as an important cure for the brutal environmental exploitation, has become a universal pursuit among higher education. Cornell University, as one of the best universities in the world, is dedicated to upgrading its campus to be more sustainable. Since the debut of the grand Climate Action Plan (CAP) in 2008, greenhouse gas emissions (GHG) have been reduced by 36% as of 2017.[1] One of the magnificent goals of the CAP is to transform the campus of Cornell University to be carbon-neutral by 2035, in which transportation is one of seven major categories of initiatives.[2] As a matter of fact, in the 2018 Sustainable Campus Index, Cornell University received poor scores in renewable energy and sustainable investment in spite of its overall gold rating.[3] Moreover, commuting vehicles had produced 28,000 metric tons of GHG in the fiscal year of 2016, accounting for 12% of the total emissions.[4] Therefore, it is then crucial to cut commuting carbon emissions to forward the development of a carbon-neutral campus. The Electric Vehicle (EV), having zero tailpipe emissions, is a perfect replacement to the traditional fossil fuel vehicle,

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[1] Cornell University, Sustainable Campus. (2019, March 20). *Greenhouse Gas Inventory: Progress*. Retrieved from https://sustainablecampus.cornell.edu/our-leadership/cap/ghg-inventory
[2] Cornell University, Sustainable Campus. (2019, March 20). *Transportation*. Retrieved from https://sustainablecampus.cornell.edu/campus-initiatives/transportation
[3] The Association for the Advancement of Sustainability in Higher Education, 2018 Sustainable Campus Index. (2018, August 22). *2018 Sustainable Campus Index: Overall Top Performers*. Retrieved from http://www.aashe.org/wp-content/uploads/2018/08/SCI-2018.pdf and https://reports.aashe.org/institutions/cornell-university-ny/report/2018-03-01/
[4] Cornell University, President's Sustainable Campus Committee. (2017, October 10). *FY 2017 Sustainability Report*. Retrieved from http://live-sustainable.pantheonsite.io/sites/default/files/2019-02/FY17%20-%20Cornell%20Sustainability%20Progress%20Report.pdf

especially in regions with low-polluting electricity sources. Therefore, the electrification of commuting vehicles on campus turns out to be a favorable trend in reducing campus carbon emissions.

This thesis, motivated by the necessity to reduce GHG emissions by commuting vehicles and improve users' convenience, is dedicated to proposing an optimal network and management of electric car charging stations on campus. As of February 2019, there are only 5 EV charging stations on Cornell campus.[5] The insufficiency of charging stations is a huge obstacle which largely curbs the vehicle electrification. Therefore, it is necessary to deploy an optimal charging station network to accelerate the process towards carbon-neutral campus given it can hugely catalyze EV development. In this thesis, a network of charging stations optimized in terms of maximizing convenience benefits and environmental benefits and minimizing construction costs is proposed. The scope of the thesis includes identifying the EV parking demand of commuting students, faculty and staff associated with buildings, estimating the parking supplies, which are capacities of parking lots, and using MIP to solve for the optimal placement and sizing of charging stations and management of EVs. The thesis is structured to first review relevant concepts, methodologies, and models from the literature, then the description and formulation of a basic model and an expanded model are demonstrated, and lastly, the results analysis is presented and discussed with a case study of Cornell University. The outputs of the models can tell us how to assign EVs from each selected building to each parking lot, which parking

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[5] Cornell University, Transportation Services. (2019, February 13). *Electric and Green Vehicle Parking*. Retrieved from https://fcs.cornell.edu/content/electric-and-green-vehicle-parking

lots will be chosen for EV charging, as well as how many charging stations to be installed in each chosen lot. A varied set of output from linearized relaxation, sensitivity analysis, and scenario analysis is presented in the demonstration of the model's capability of planning the charging stations with varying emphasis on different objectives or assumed parameters, fulfilling the objective of the thesis.

1.2 Literature Review

The electrification of transportation is an encouraging trend to considerably tackle the critical climate change issue (Yong, Ramachandaramurthy, Tan, and Mithulananthan, 2015). More specifically, introduction of electric vehicles (EVs), consisting of hybrid electric vehicle (HEV), fuel cell electric vehicle (FCEV), battery electric vehicle (BEV), and plug-in electric vehicle (PEV), in the transportation systems can significantly cut the carbon emission (Amjad, Ahmad, Rehmani, and Umer, 2018; Basu, Tatiya, and Bhattacharya, 2019). Not only are EVs impactful in the perspective of the environment, but also the commercial area. BloombergNEF's latest report forecasts that EV sales are likely to increase by a factor of 60 from 2017 to 2040, as of which EVs account for 33% of the global fleet.[6] In the face of the unprecedented transformation towards green mobility, charging infrastructure would become either a powerful booster or a main obstacle to EV adoption.

Motivated by its enormous business prospects, there are plenty of innovations in charging infrastructure. Chen, He, and Yin (2016) have proposed a novel user equilibrium model to optimize the process of deploying an emerging charging-while-

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[6] Bloomberg New Energy Finance, Electric Vehicle Outlook 2018. (2018). *Electric Vehicle Outlook 2018: Global sales outlook* (Report No. 3). Retrieved from https://bnef.turtl.co/story/evo2018

driving technology - Charging lanes. Also, battery swapping is a non-negligible business model which provides the service of replacing batteries for EVs in just a moment instead of time-consuming charging (Mak, Rong, and Shen, 2013). Mak et al. (2013) have carefully developed a robust optimization for the deployment of battery-swapping infrastructure considering its following prospective impacts and further possible advancements as well. Yang, Guo and Zhang (2017) have defined an EV swapping network design with the customer satisfaction including “range anxiety” and “loss anxiety”, and then solved this model with the combination of Tabu Search and GRASP. Given the high-profile sharing economy, autonomous technology and electrifying transportation, shared autonomous electric vehicles would be a reasonable innovation by a combination. Brandstätter, Kahr, and Leitne (2017) have studied the charging placement of an electric car-sharing system by solving a two-stage stochastic optimization via an MIP with a heuristic algorithm. The research by Iacobucci, McLellan, and Tezuka (2019) has devised an approach to optimize the charging of autonomous on demand EV network taking vehicle-to-grid, routing and relocation into consideration.

Although the charging innovations as mentioned above are cutting-edge and attractive, EV charging stations remain prevalent because of their relatively lower cost, more stable functionality and more widespread adoption. Accordingly, it is particularly vital to address the issue of deploying charging stations and designing an optimal charging network considering the cost of investment, user experience, and environmental benefits. Dashora et al. (2010) have designed an MIP model to solve the PHEV charging infrastructure planning (PCIP) problem for workplaces. Moreover, with a case study, he validates the methodology and proves the necessity to consider user convenience and grid connections in the model.

It is not hard to find out that the previous MIP problems fall into the category of the NP-hard problems, which means that no polynomial-time algorithm exists (Garey, and Johnson, 2009). Therefore, a variety of approaches have been introduced to surmount this big obstacle.

Initially, the relaxation of a particular model component would be a fair remedy. Thiongane, Cordeau, and Gendron (2015) have compared several relaxations including Lagrangian relaxation, linear programming relaxations, and partial relaxations of the integrality constraints in the fixed-charge capacitated multicommodity network design (CMND) problem. Tran, Nagy, Nguyen, and Wassan (2018) have leveraged the linear relaxation results as initial candidates for an effective heuristic algorithm, which exchanges them with the remaining sets via parallel computing. It turns out to cost less time compared to CPLEX in obtaining the optimal solutions.

Heuristic algorithms and meta-heuristics methods are mainstreamed techniques to find straightforward and satisfactory solutions for various complex NP-hard problems (Amjad et al., 2018).

Tabu Search, a metaheuristic algorithm, is specifically proposed to avoid the trap of local optimality (Crainic, Gendreau, and Farvolden, 2000). Crainic et al. (2000) have applied a Simplex-based Tabu Search framework that utilizes the combination of pivot moves and column generation to efficiently solve the CMND problem. Moreover, researchers have continually strived to push the performance of heuristic approaches to their limits. A combining exact and heuristic method (Hewitt, Nemhauser, and Savelsbergh, 2010) has been developed through the neighborhood search, linear programming relaxation, and randomization to produce a verifiable good candidate sets in no time for the fixed-charge network flow problem.

In addition to the Tabu Search, several heuristic algorithms have been put in an application to overcome the NP-hard problems partially. Xu, Miao, Zhang, and Shi (2013) have adopted a modified binary Particle Swarm Optimization (PSO) based on Taboo Mechanism to obtain the optimal deployment of centralized charging stations. A genetic algorithm-based method has been employed to determine the locations of charging stations and the demands of chargers per charging station with the objective of minimizing the total cost (Zhu, Gao, Zheng, and Du, 2016). Chouman, Crainic, and Gendron (2017) have proposed a cutting-plane algorithm, which is integrated with five valid inequalities, to solve the CMND problem.

The deployment of charging infrastructure has been a hot field of operations research since 2010 (Zhu et al., 2016). It is noticeable that intensifying efforts have been made to incorporate more and more realistic factors for a more practical model application. Research by He, Kuo, and Wu (2016) has applied interviews with key stakeholders to test different model performances. Guo, Deride, and Fan (2016) have researched on the interactive structure including several agents, investors, and travelers via a network-based multi-agent optimization modeling framework. Andrenacci, Ragona, and Valenti (2016) have applied cluster analysis to simplify the charging demands to find the optimal charging location.

The interactive and synergistic effect between charging infrastructure and the electrical grid has been a newly prominent topic in this research field. A game theoretical framework (He, Wu, Yin & Guan, 2013), which builds up an equilibrium model among charging network, traffic flow, and electricity network, has been derived to optimally allocate public charging stations via an active-set algorithm. Research by Hasapis et al. (2017) has specified the main steps in the design of large-scale photovoltaic power generation plants in University campuses, which facilitate some relevant sustainable technological improvements like EVs.

When it comes to an optimal charging station network, the environmental issue is a palpable aspect. Shahraki, Cai, Turkay, and Xu (2015) have maximized the vehicle-miles-traveled being electrified in a carefully tuned CPLEX model with large-scale taxi trajectory data of Beijing as inputs. Tu et al. (2016) have evaluated the reduced carbon emissions from the deployment of charging. Levinson and West (2018) have applied both scenario and parametric analysis to explore the environmental impacts of EV charging infrastructure.

1.3 Research Roadmap

To give a big picture of this thesis and formulate a streamlined application process, the research roadmap is as follows:

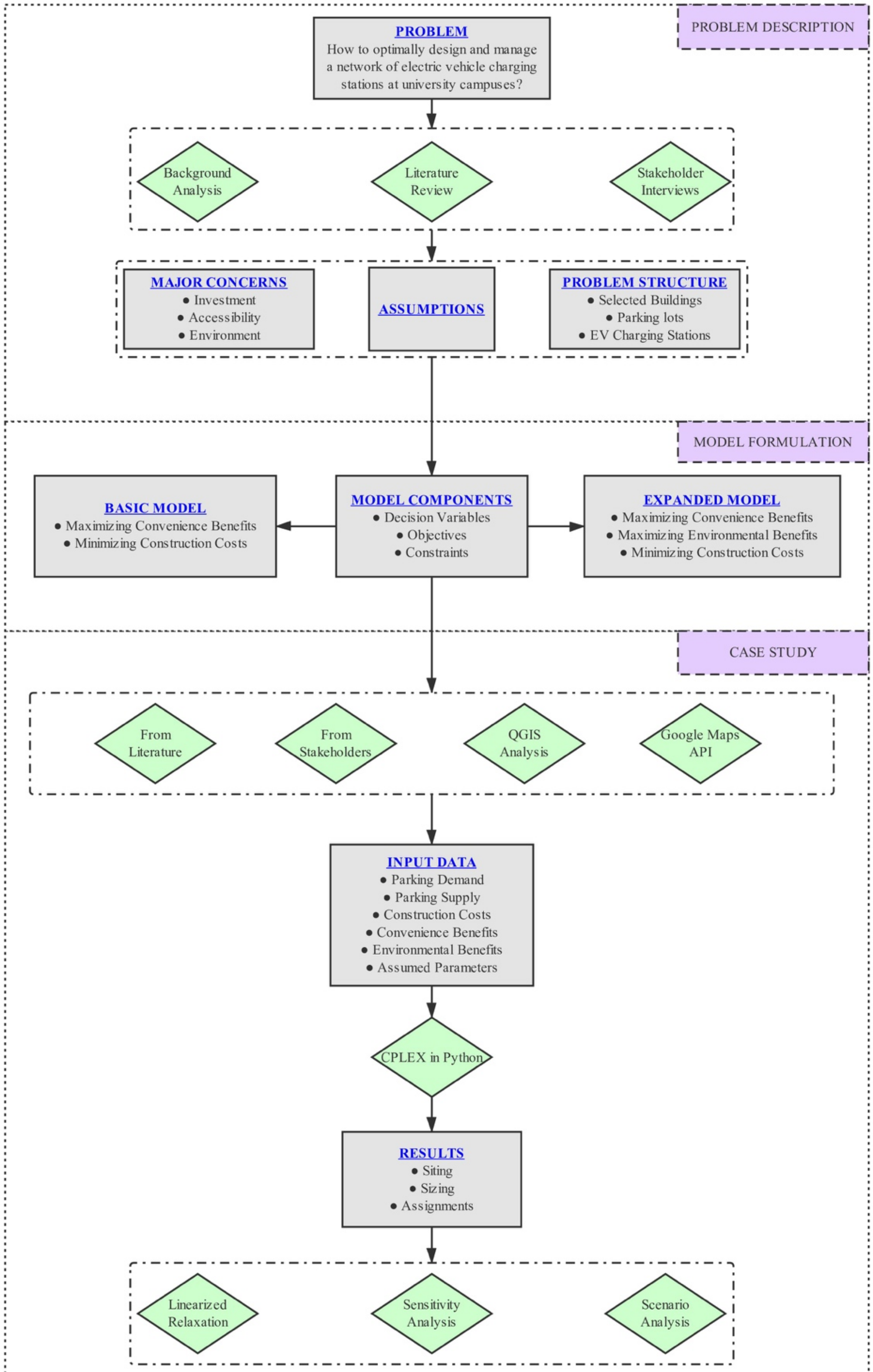

Figure 1: Research roadmap

CHAPTER 2

PROBLEM DESCRIPTION

Providing the absolute indispensability of charging infrastructure in facilitating the popularization of EVs, where to place the charging stations, how many chargers needed for one charging station, and how to optimally assign parking demand become our priority tasks. Dashora (2010) has recognized that a day-time charging infrastructure in workplaces is critical to alleviate EV owners' range anxiety and therefore significantly accelerate the electric vehicle adoption. Moreover, the U.S Department of Energy has deliberately promoted campus charging through several published handbooks, which point out its immense significance for the community, environment, and research. Therefore, in this thesis, we study the application of implementing an approximately optimal charging network for EVs in workplaces like university campuses.

2.1 Major Assumptions

A well-organized and compendious model cannot be constructed without reasonable assumptions. In order to simplify our model and concentrate on the key aspects, we make some appropriate assumptions about our model in this thesis as follows:

1. The necessary input data like coordinates, capacities of parking lots and the distribution of daily driving range is available through stakeholders or reasonable estimation.

2. The operational days of charging station network in this thesis are 2400 days, which is 10 years with 240 days of use per year on average.[7]
3. Users walk between selected buildings and parking lots twice per day averagely.

It is reasonable to assume this frequency because most users walk from parking lots to selected buildings in the morning and walk from selected buildings to parking lots in the evening.

4. The EVs are considered homogenous.

All of the essential features of EVs studied in this thesis including battery range, types of charging connector and charging time are the same so as to avoid unnecessary analysis.

5. One charger can only be used by one EV at a time instead of being shared by several EV simultaneously.

Although some new charging solutions like ClipperCreek's Share2®, which enable two EV charging stations to share power from one branch circuit,[8] look promising, it is costly and possibly unstable to adopt them right now. Therefore, in this thesis, we only consider the most commonly used charging products, which means that one charger can only be used by one EV at a time.

6. All of the parking demands originate from our selected buildings.

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[7] Brown, A. National Renewable Energy Laboratory. (2014, November 18). *Workplace Charging: Comparison of Sustainable Commuting Options*. Retrieved from https://afdc.energy.gov/files/u/publication/Session1B_Brown.pdf

[8] Guinn, S. (2016, September 8). *ClipperCreek, Inc. Announces New Power Sharing Electric Vehicle Charging Stations*. Retrieved from https://www.clippercreek.com/new-power-sharing-electric-vehicle-charging-stations/

Since many buildings on campus are very close, we can cluster the neighboring buildings and select some representative ones, which will hugely decrease the difficulty of NP-Hard optimization.

7. For each selected building,

$$\frac{\text{The number of vehicles associated with the building}}{\text{Total number of vehicles on campus}} = \frac{\text{The building's net area}}{\text{Summation of all buildings' net area}}$$

Since we cannot get the data of exact number of vehicles associated with each building, but we know the total number of parking permits on campus, we decide to use building's net area to estimate each building's parking demand.

8. For all selected buildings in a given year,

$$\text{The rate of EV penetration} = Fixed\ Constant$$

In a given year, we assume that the rate of EV penetration is a constant among all selected buildings which will avoids trivia computation.

9. For each parking lot,

$$\frac{\text{maximum EV parking spaces}}{\text{parking lot capacity}} = Fixed\ Constant$$

In the light of the Transportation Equity, EVs are not supposed to occupy a whole parking lot, which precludes traditional fossil fuel vehicles from parking at all. Consequently, it is necessary to set another parking capacity for EVs in each parking lot, which preserves the parking equity finely.

2.2 Problem Structure

To refine this problem mathematically, first and foremost we decompose it and identify the critical components of the structure. The research focus of this thesis is on the workplaces like university campuses, where thousands of students, faculty, and staff are respectively associated with one of the scattered buildings on campus. Given this unexampled challenge and central importance in the network management for operators like the university, it is then important for us to optimally manage EVs considering environmental benefits, user convenience, and construction costs partially or fully.

We recognize three core components of this problem as follows.

2.2.1 Selected Buildings

To understand the parking demand side of this problem, it is needful to cluster the demands to some selected buildings and assign them to parking lots appropriately. Hence, we are supposed to obtain:

- The geographical coordinates of the selected buildings.
- The EV charging demands associated with each selected building.

2.2.2 Parking Lots

As for the parking supply side of the problem, we decide to install charging stations on parking lots. Since there are so many scattered parking lots on campus, we can cluster them based on relative distance. The following input data are collected:

- The geographical coordinates of the selected parking lots.
- The capacity of each lot.

2.2.3 EV Charging Stations

For each parking lot, it is required to determine whether the lot should be chosen for EV charging stations, which would incur a fixed cost of connecting with the electric grid network, and how many charging stations to be installed if it is chosen. Therefore, we need to find out:

- Whether to install charging stations in each parking lot.
- The number of charging stations installed in each parking lot.
- The cost of installing electric transformer in a parking lot and connecting to the electric grid network.
- The cost of installing and operating one charging station.

2.3 Notations

To better formalize this problem, before anything else all notations should be specified as follows:

B Sets of selected buildings: i.e., the sets of the centroids of the clustered buildings on campus;

L Sets of parking lots: i.e., the sets of the centroids of the clustered parking lots on campus;

N_B Numbers of set B;

N_L Numbers of set L;

b Selected building b, $\forall b \in B$;

l Parking lot l, $\forall l \in L$;

C^S Cost of installing and operating ONE charging station;

C^G Cost of installing electric transformer and connecting ONE parking lot to the grid network;

q_l Installation capacity of a parking lot l;

ρ Service level of charging station network;

P_b Number of EVs associated with selected building b;

$\bar{t}$ Average walking time from parking lots to buildings on campus;

t_{bl} Walking time from a selected building b to a parking lot l;

t^{MAX} Maximum acceptable walking time;

O The operational days of charging station network. An assumption is 2400 days in total;

F A user's average walking frequency between selected buildings and parking lots. An assumption is 2 times per day.

CHAPTER 3

MODEL FORMULATION

Based on our analytic decomposition of the problem structure in CHAPTER 2, we can construct a Mixed Integer Programming (MIP) optimization problem. In order to model an optimization problem solidly and mathematically, it is critical to identify the decision variables, objectives and constraints accurately.

3.1 Decision Variables

To design an optimal charging station network, we set up two decision variables as follows:

1. For each parking lot, whether being chosen for installing EV charging stations - Binary variables
2. For each parking lot, the number of charging stations installed - Integer variables

To provide an essential and practical operating guideline for network management, which is usually for stakeholders like the university, we set up one decision variable as follow:

3. The number of EVs assigned from each selected building to each selected parking lot - Integer variables

In summary, the notations of the three decision variables are as follows:

I_l Binary variable of whether to install charging stations at parking lot l;

X_l Integer variable of number of charging stations installed at parking lot l;

A_{bl} Integer variable of number of EVs assigned from selected building b to parking lot l.

3.2 Objectives

For the basic model, our goal is to maximize overall benefits brought by implementing this charging station network. To be more specific, two sub-objectives about user convenience and construction costs have been taken into consideration as detailed below:

1. Maximize the convenience benefits

This objective refers to maximizing the total reduced walking time of users from their selected buildings to their assigned parking lots in the whole operational years. Greater user convenience is the key for better user experience, which leads to broader user acceptance. Moreover, greater user acceptance provides the guarantee for stable returns and accordingly the sustainable development of our charging station network at campuses. For this reason, it is essential to maximize the convenience for users.

2. Minimize the construction costs

The construction costs in our analysis include costs of connecting parking lots to electric grid network and installing and operating EV charging stations. The objective of minimizing the construction costs is out of consideration for the limited budget of universities. Let's take Cornell University as an example. Although the capital budget of Cornell University in FY2019 is $930,459,348, which is a substantial number among American universities, this is actually for 125 projects across three campuses in nearly all aspects. [9] Therefore, it is critical to keep the costs down for the unanimous approval from decision makers and continuing investment in this project.

From the above analysis, we can see that the construction cost is in US Dollar (USD), whereas the unit of convenience benefits is the hour. The discrepancy in the dimensions and magnitudes between two objectives makes directly combining two objectives lose capability in maximizing overall benefits with different weight values. Therefore, we decide to transform the convenience objective to a monetized value of travel time (in USD). According to the report of the U.S. Department of Transportation, the monetized value of travel time by walking is \$29.5/hour.[10] Accordingly, we can transform the walking time to a monetized value, which is in alignment with the construction cost.

In sum, we adjust the original time value to monetized value with transforming factor as follow:

M Monetization factor transforming the time value to the monetized value. An assumption is \$29.5/hour.

3.3 Constraints

Well-defined constraints are indispensable for a well-represented optimization model. We adopt the constraints in Dashora et al. (2010) for our basic model as shown below:

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[9] Cornell University, Division of Budget and Planning. (2018, March 8). *FY2019 Capital Budget with Projected Five Year Spend by Funding Source*. Retrieved from https://internal.dpb.cornell.edu/LongviewCapitalReports/index.html

[10] U.S. Department of Transportation, Office of the Secretary. (2018, December). *Benefit-Cost Analysis Guidance for Discretionary Grant Programs*. Retrieved from https://www.transportation.gov/office-policy/transportation-policy/benefit-cost-analysis-guidance-2017

1. The constraints of binary and integer decision variables;
2. For each parking lot, the number of charging stations installed must not exceed its EV capacity;
3. The whole charging station network must fulfill a predetermined service level, i.e., it must at least serve a fixed percentage of EV charging demands;
4. For each selected building, all EVs associated with it must be given explicit parking assignments;
5. We must not assign an EV to a parking lot which is beyond the predefined maximum acceptable walking time.

3.4 Basic Model

After carefully analyzing the structure of our problem and the decision variables, objectives and constraints, we can construct the mathematical model as below:

Basic Model **max** $$\omega_1\left(M \cdot O \cdot F \sum_{b=1}^{N_B}\sum_{l=1}^{N_L}(\bar{t} - t_{bl})A_{bl}\right) - \omega_2 \sum_{l=1}^{N_L}(C^S X_l + C^G I_l) \qquad (1)$$

$$s.t. \quad X_l \le q_l I_l \qquad \forall l \in L \qquad (2)$$

$$\rho \sum_{b=1}^{N_B} A_{bl} \le X_l \qquad \forall l \in L \qquad (3)$$

$$\sum_{l=1}^{N_L} A_{bl} = P_b \qquad \forall b \in B \qquad (4)$$

$$A_{bl} = 0, if\ t_{bl} \ge t^{MAX} \qquad \forall b \in B, \forall l \in L. \qquad (5)$$

$$A_{bl},\ X_l \ge 0(Integer), I_l \in \{0,1\} \quad \forall b \in B, \forall l \in L \qquad (6)$$

Where ω_1, ω_2 are the weights of two objectives: i.e., $\omega_1 + \omega_2 = 1$. The objective function (1) is a combination of our two sub-objectives – Maximizing convenience benefits and minimizing construction cost. Note that the cost part includes a fixed electric connecting cost if one parking lot is chosen for installation of charging stations. Moreover, for the convenience part, we apply *O* (Total operational days) and *F* (A user's average walking frequency per day) to calculate the total reduced walking time in all operational years, transformed by *M* (Monetization factor) to be monetized value. Constraints (2) are capacity constraints, which mean that if parking lot *l* is chosen to install charging stations, there is a capacity for how many charging stations we can install. Constraints (3) are service level constraints. Considering maximizing the system usage, it makes sense to maintain a predetermined service level to guarantee a fully used network. Constraints (4) are requirements that all EVs should be given explicit assignments on where to park. Constraints (5) are convenience constraints, which require all EVs should not be given assignments beyond the maximum acceptable walking time. Constraints (6) specify this mathematic model as an integer programming problem (includes binary variables).

3.5 Model Expansion

After carrying out a face-to-face interview with one of the key stakeholders – Cornell University Transportation and Delivery Services, it has been learned that environmental benefits from implementing this charging station network and delicacy management of this network are also in their major concerns. To respond to this demand, it calls for an appropriate modification and expansion in our basic model. It is noticeable that although we assume all EVs are homogenous, the commuting distance is different among all drivers. Accordingly, it is natural to classify all EVs based on their commuting distances for delicacy network management. Furthermore, giving priority in charging to those EVs with longer commuting distances brings greater environmental benefits in carbon emission. In consequence, we can modify and expand our basic model as detailed below.

3.5.1 Additional Assumption

To accurately quantify the environmental benefits brought by this charging station network, we make an additional assumption that every installed charging station will only serve one EV per day and there will be no vacancy in this network. This assumption is reasonable because most users in workplace are not willing to move their vehicles during the day and the service level is below 100%. Therefore, we can introduce the following serving ratio:

r Serving ratio: i.e., number of EVs served by one charging station in one day. An assumption is 1 EV/station;

3.5.2 Additional Notations

To tactically assign all EVs and manage our charging station network effectively, we classify all EVs according to the distribution of commuting distances. In order to reflect this change and represent our expanded model properly, we add additional notations as follows:

C Classes of EVs: i.e., classes of EVs categorized by the distribution of commuting distances;

N_C Numbers of set C;

c Class c of EVs, $\forall c \in C$;

P_{bc} Number of EVs in class c associated with selected building b;

R_c The reduction of carbon emissions by one EV in class c per day;

S Social benefit of reduced carbon emissions in dollars.

3.5.3 *Modified Decision Variables*

To provide more specific assignments for a delicacy network management, which complies with the requirement for greater environmental gain, we modify the decision variable as follow:

A_{blc} Integer variable of number of EVs in class c assigned from a selected building b to a parking lot l;

X_{lc} Integer variable of number of charging stations in a parking lot l giving parking priority to EVs in class c.

3.5.4 *Expanded Model*

After adding additional notations and modifying decision variables, we are able to construct our expanded model as presented below:

Expanded Model

$$\max \ \omega_1\left(M\cdot O\cdot F\sum_{b=1}^{N_B}\sum_{l=1}^{N_L}\sum_{c=1}^{N_C}(\bar{t}-t_{bl})A_{blc}\right)+\omega_2\left(S\cdot O\sum_{l=1}^{N_L}\sum_{c=1}^{N_C}R_c\cdot r\cdot X_{lc}\right)-\omega_3\sum_{l=1}^{N_L}\left(C^S\sum_{c=1}^{N_C}X_{lc}+C^G I_l\right) \quad (1')$$

$$s.t. \quad \sum_{c=1}^{N_C}X_{lc}\le q_l I_l \qquad \forall l\in L \quad (2')$$

$$\rho\sum_{b=1}^{N_B}\sum_{c=1}^{N_C}A_{blc}\le\sum_{c=1}^{N_C}X_{lc} \qquad \forall l\in L \quad (3')$$

$$X_{lc}\le\sum_{b=1}^{N_B}A_{blc} \qquad \forall l\in L,\forall c\in C \quad (4')$$

$$\sum_{l=1}^{N_L}A_{blc}=P_{bc} \qquad \forall b\in B,\forall c\in C \quad (5')$$

$$A_{blc}=0, if\ t_{bl}\ge t^{MAX} \qquad \forall b\in B,\forall l\in L,\forall c\in C \quad (6')$$

$$A_{blc},\ X_{lc}\ge 0(Integer), I_l\in\{0,1\} \qquad \forall b\in B,\forall l\in L,\forall c\in C \quad (7')$$

Where $\omega_1, \omega_2, \omega_3$ are the weights of three objectives: i.e., $\omega_1 + \omega_2 + \omega_3 = 1$. The objective function (1') is a combination of three sub-objectives – Maximizing convenience benefits and environmental benefits and minimizing construction cost. For the newly added environmental benefits part, we utilize R_c (The reduction of carbon emissions by one EV in class *c* per day), O (Total operational days), and *r* (number of EVs served by one charging station in one day) to calculate the total reduced carbon emissions in all operational years, transformed by S (Monetization factor) to be monetized value. Constraints (2') are still capacity constraints, though we use the summation of X_{lc} in different EV classes. Constraints (3') are service level constraints considering the summation of EVs in different classes. Constraints (4') come from the definition of X_{lc}, which present that the number of charging stations installed giving parking priorities to a specific EV class should not exceed the number of EVs in that class assigned to this parking lot. Constraints (5') are requirements that EVs in each class should be given explicit assignments on parking lots. Constraints (6') are convenience constraints taking classes of EVs into account. Constraints (7') are integer and binary constraints like before.

CHAPTER 4

CASE STUDY

After proposing the basic model and expanded model in CHAPTER 3, it is essential to evaluate their practicality and effectiveness with a specific case study at Cornell University's campus.

4.1 Data Preparation

To solve models in this specific case study, many data are required as inputs of the models. We employ various methods to obtain reliable input data of different categories as detailed below.

4.1.1 Parking Demand

1. Geographical coordinates of selected buildings on campus

We find the ArcGIS Online map of Cornell University's campus[11] and then extract its source link via the *Sources* in Chrome browser's *Developer Tools*,[12] with which we can import all feature maps into QGIS3 via *ArcGIS Feature Server*. After adding the polygon layer of 297 buildings on campus, before all else, we need to use the tool *Fix Geometries* to fix the invalid geometry. Afterward, we can generate centroids of each building with the tool *Centroids*, and cluster these centroids to be 50 groups using the tool *K-means clustering* (See as Table 1 in APPENDIX A). After calculating the *Mean Coordinates* of each group and changing the coordinate system

[11] Cornell University, Cornell Campus Planning Department. (2019, March 3). *Accessibility at Cornell Univerisity*. Retrieved from https://cornell.maps.arcgis.com/apps/MapSeries/index.html?appid=80e7ca4d43d6496892de80b5e699e1d1

[12] https://gis.fcs.cornell.edu/arcgis/rest/services/Production/

to *WGS 84*, finally, we obtain the geographical coordinates of selected buildings on campus. (See as Table 2 in APPENDIX A)

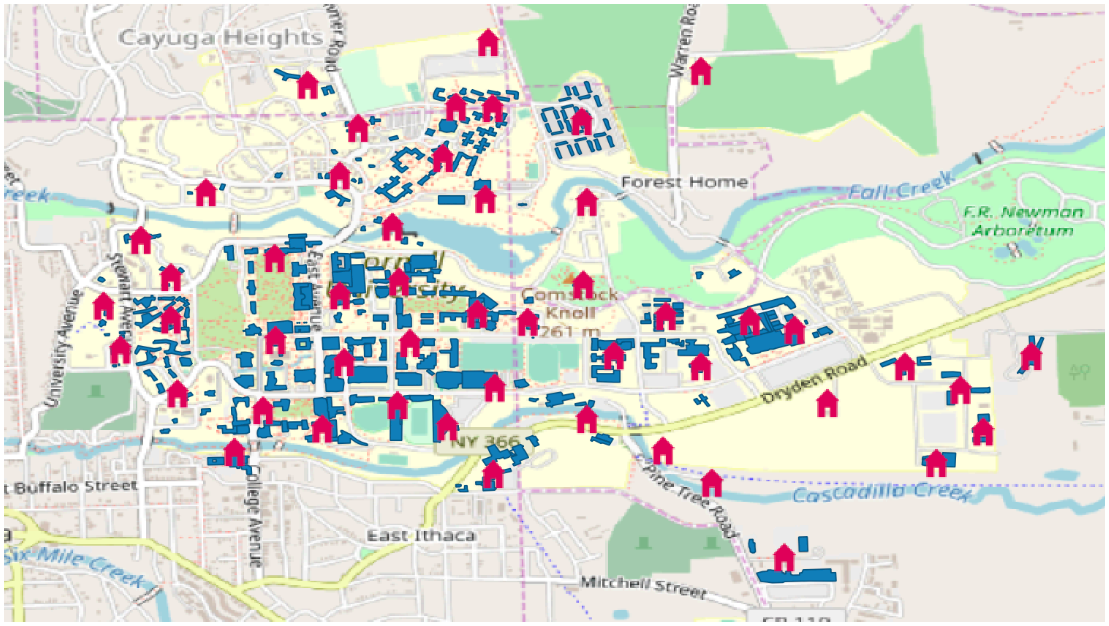

Figure 2: Layout of selected clustering buildings on campus

2. Net area of each selected building

With the square footage of buildings provided by Cornell University Transportation and Delivery Services, we can calculate the total net area of each selected building using the *SUMIF* function in Excel (See as Table 2 in APPENDIX A).

3. Total parking demands

Based on the detailed information of parking permits from Cornell University Transportation and Delivery Services, we consider 11,840 vehicles based on campus which might require parking service (Including vehicles associated with university departments, employees, students, and employees of affiliated organizations based on campus).

4.1.2 Parking Supply

1. Geographical coordinates and installation capacities of parking lots on campus

We import the feature maps of parking lots into QGIS3 via ArcGIS Feature Server, which include one outline map of parking lots and the other of detailed parking space. First of all, we fix those invalid geometries of both layers. Then, we generate centroids of each parking space and each parking lot. Afterward, we can apply *Count points in polygon* to count the number of parking space in each parking lot. Next, we cluster the centroids in the outline map to be 80 groups. After calculating the mean coordinates of each group and pairing the parking space with those groups, eventually, we obtain the geographical coordinates and installation capacities of parking lots on campus (See as Table 3 in APPENDIX A).

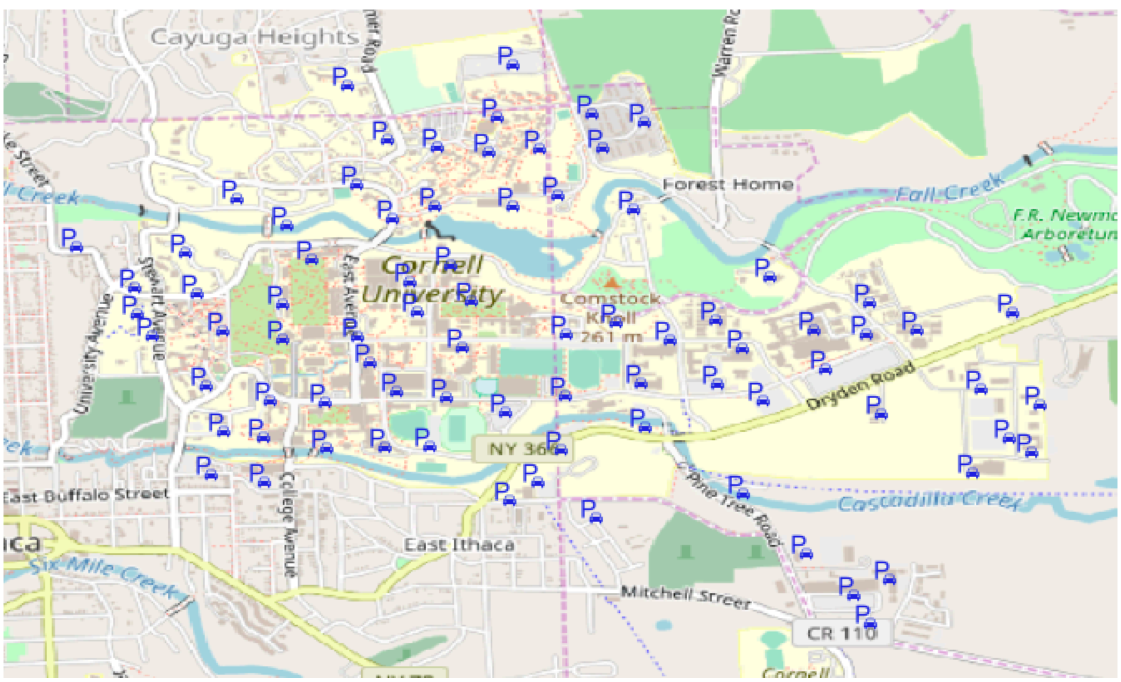

Figure 3: Layout of clustering parking lots

4.1.3 Construction Costs

1. Cost of connecting ONE parking lot to the grid network (C^G) and installing and operating ONE charging station (C^S)

There are majorly three types of Electric Vehicle Supply Equipment (EVSE) on the market, which are Level 1 EVSE, Level 2 EVSE, and DC fast-charging EVSE.[13] The main differences between them are costs and charging rates. Level 1 EVSE is the least expensive one, but it may only charge one EV per workday. Implementing DC fast-charging EVSE is the most expensive choice although it maintains the fastest charging rate. Considering the following points: (1) Drivers in workplaces like university campuses are expected to park for a long period even a whole day every workday;[14] (2) Most EVs in U.S. can use Level 1 or Level 2 EVSE instead of DC fast-charging stations[15]; (3) Universities normally want to keep the construction costs down, we decide to choose Level 1 stations to implement our charging station network. The Level 1 EVSE unit cost range (single port) is \$300-\$4,500, the installation cost range for DC EVSE is \$10,000-\$25,000,[16] and the operating cost per port is \$600.[17] Taking into consideration that we plan to install a

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[13] U.S. Department of Energy, Alternative Fuels Data Center. (2019, March 3). *Installing Workplace Charging.* Retrieved from https://afdc.energy.gov/fuels/electricity_charging_workplace.html
[14] U.S. Department of Energy, Energy Efficiency & Renewable Energy. (2016, March). *Workplace Charging: Charging Up University Campuses*. Retrieved from https://afdc.energy.gov/files/u/publication/wpc_charging_university_campuses.pdf
[15] U.S. Department of Energy, Energy Efficiency & Renewable Energy. (2019, March 3). *Plug-In Electric Vehicle Handbook for Workplace Charging Hosts*. Retrieved from https://afdc.energy.gov/files/u/publication/pev_workplace_charging_hosts.pdf
[16] U.S. Department of Energy, Energy Efficiency & Renewable Energy. (2015, November). *Costs Associated with Non-Residential Electric Vehicle Supply Equipment - Factors to consider in the implementation of electric vehicle charging stations*. Retrieved from https://afdc.energy.gov/files/u/publication/evse_cost_report_2015.pdf
[17] Vermont Energy Investment Corporation. (2014, June). *Electric Vehicle Charging Station Guidebook: Planning for Installation and Operation.* Retrieved from https://www.driveelectricvt.com/Media/Default/docs/electric-vehicle-charging-station-guidebook.pdf

functional charging station network, which means many stations would be implemented, we are likely to get a wholesale price for chargers but a very high cost in connecting to grid network. Consequently, it is reasonable to set the C^G at $12,500 and the C^S at $1500.

4.1.4 Convenience Benefits

1. Average walking time from parking lots to buildings on campus ($\bar{t}$)

According to one report by Cornell University, 30% of the campus parking supply is located within a 5~7-minute walking distance of the central campus.[18] As most buildings are located in the central campus, we can assume $\bar{t}$ equals to 6 minutes.

2. The matrix of walking time from selected buildings to parking lots (t_{bl})

Since we have already obtained the geographical coordinates of all selected buildings and parking lots, we decide to make use of *Distance Matrix API* on Google Map Platform to calculate the matrix of walking time from selected buildings to parking lots (See as Table 4 in APPENDIX A). The code is also shown as Source Code 1 in APPENDIX B.

3. Maximum acceptable walking time (t^{MAX})

According to Yang, & Diez-Roux (2012), 0.25 miles is commonly used by researchers as a maximum acceptable walking distance in the United States. Moreover, the preferring walking speed is 1.4 m/s (Browning, Baker, Herron, & Kram, 2006). Then, we can calculate the acceptable walking time as 5 minutes approximately. However, many of the parking lots at Cornell are located far from the

[18] Trowbridge & Wolf, LLP. (2008, July 15). *DRAFT: transportation-focused Generic Environmental Impact Statement (t-GEIS).*

central campus, where most employees work. Hence, we decide to set the maximum acceptable walking time as 10 minutes for the initial calculation.

4.1.5 Environmental Benefits

1. The social benefit of reduced carbon emissions in dollars (S)

According to a report by United States Environmental Protection Agency, the recommended monetized value of reduced carbon emissions is $42 per metric ton of CO_2 in the year of 2020.[19] However, another report by Stanford University says the actual social cost of carbon is $220 per metric ton of CO_2, which includes more necessary factors in the calculation.[20] Since our ultimate concern for this thesis is about environment, $220 per metric ton of CO_2 is chosen as the social benefit in this study.

2. Classes of vehicles based on the commuting distance

We are given the distribution of employees' commuting distances from Cornell University Transportation and Delivery Services (See as Table 5 in APPENDIX A). Therefore, we can aggregate this distribution to be 6 classes as follows:

Class	Commuting Distance	Percent	Estimated Average Commuting Distance
1	60 or more miles	0.7%	60 miles
2	40 to 59 miles	2.1%	48.3 miles
3	20 to 39 miles	11.2%	27.9 miles
4	10 to 19 miles	24.2%	12.9 miles
5	5 to 9 miles	18.5%	7.5 miles
6	Less than 5 miles	43.3%	2.5 miles

Table 6: Classes of EVs

[19] United States Environmental Protection Agency. (2016, December). *Social Cost of Carbon.* Retrieved from https://www.epa.gov/sites/production/files/2016-12/documents/social_cost_of_carbon_fact_sheet.pdf

[20] Moore, F. C., & Diaz, D. B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. Nature Climate Change, 5(2), 127. Retrieved from https://news.stanford.edu/news/2015/january/emissions-social-costs-011215.html

3. The reduction of carbon emissions by one EV in each class per day (R_c)

Although EVs in all-electric mode produce zero tailpipe emissions, there are carbon emissions from electric utilities for charging.[21] In Ithaca, NY, where Cornell University locates, the average carbon emissions of the gasoline-only vehicle are 381 grams of CO_2e[22] per mile, while those of plug-in hybrid EV (PHEV) are 155 grams of CO_2e per mile and those of battery EV (BEV) are 54 grams of CO_2e per mile.[23] Let's assume the market shares of PHEV and BEV are 50% and 50% respectively for our initial calculation. Then, the average carbon emissions of EV in Ithaca should be 104.5 grams per mile. Moreover, it is fair to assume users will have two commutes per workday (round trip between home and campus every workday). Consequently, we can calculate the reduction of carbon emissions by one EV in each class per day as shown below:

Class	Estimated Average Commuting Distance (miles)	R_c (grams)
1	60	12540
2	48.3	10094
3	27.9	5832
4	12.9	2696
5	7.5	1568
6	2.5	522

Table 7: The reduction of carbon emissions by one EV in each class per day

4.1.6 Assumed Parameters

1. Weights of different sub-objectives ($\omega_1,\ \omega_2,\ \omega_3$)

[21] U.S. Department of Energy, Alternative Fuels Data Center. (2019, March 5). *Direct and Well-to-Wheel Emissions.* Retrieved from https://afdc.energy.gov/vehicles/electric_emissions.html
[22] CO_2e is short for "carbon dioxide equivalent", which is a standard unit for measuring all of a vehicle's greenhouse gas emissions.
[23] Union of Concerned Scientists. (2019, March 5). *How Clean is Your Electric Vehicle?* Retrieved from https://www.ucsusa.org/clean-vehicles/electric-vehicles/ev-emissions-tool#z/14850/_/_/_

In the basic model, we set $\omega_1 = 0.2,\ \omega_2 = 0.8$ for the initial calculation because we care more about construction costs than convenience benefits, whereas we assume $\omega_1 = 0.1, \omega_2 = 0.7, \omega_3 = 0.2$ in the expanded model because our ultimate motivation for this study is about environment and Cornell University has quite a lot funding for sustainable development.

2. The service level of the charging station network (ρ)

   we set the value as 70% for the initial calculation.

3. The rate of EV penetration

   The market share of EV in New York State is 1.03%.[24] So we set the rate of EV penetration as 1.00% for the initial calculation.

4.2 Model Solving

In solving this optimization model, we have tried Glop, Pulp, and CPLEX. Trials show that CPLEX works best for this problem. Therefore, we determine to apply CPLEX based on Python to solve our models. The model solving has been conducted on a MacBook Pro with 3.1 GHz Intel Core i5 CPU and 16 GB 2133 MHz LPDDR3.

4.2.1 For Basic Model

After running our code in Python (See as Source Code 2 in APPENDIX B), we determine that this model is eligible and obtain reasonable results as follows:

In Table 8, all 115 EVs have been assigned to specific parking lots as we design. 24 out of 80 parking lots are chosen to install charging stations, which works

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[24] EVAdoption. (2017). *EV Market Share by State*. Retrieved from https://evadoption.com/ev-market-share/ev-market-share-state/

towards our goal of keeping down construction costs. 87 charging stations have been installed to maintain our target service level. The monetized value of convenience benefits is quite high because most of the chosen parking lots are located in the central campus which is close to many buildings, and the time value of walking is also quite high. Moreover, we can see that the overall benefits are negative, which means the current scenario is economic infeasible. This is because we place a larger weight on construction costs and now the convenience benefits are not high enough because of the small number of EVs.

	Initial Calculation
Number of EVs	115
Number of Assigned EVs	115
Number of Parking Lots Chosen	24
Total Parking Capacity for EVs	271
Number of Charging Stations Installed	87
Maximum Charging Stations in a Chosen Parking Lot	8
Minimum Charging Stations in a Chosen Parking Lot	1
Convenience Benefits ($)	801062
Construction Cost ($)	430500
Overall Benefits ($)	-184187

Table 8: Numeric results from the initial calculation (Basic Model)

In Figure 4, parking lots chosen are illustrated by sized text diagrams, while the blue parking symbol signs refer to unchosen parking lots. We can tell that most of the chosen parking lots locate at the central campus, which maximizes the convenience of users. Moreover, we can notice that one parking lot in the east campus is only installed one charging station, because this is the only parking lot within maximum acceptable walking time which can serve the one neighboring EV.

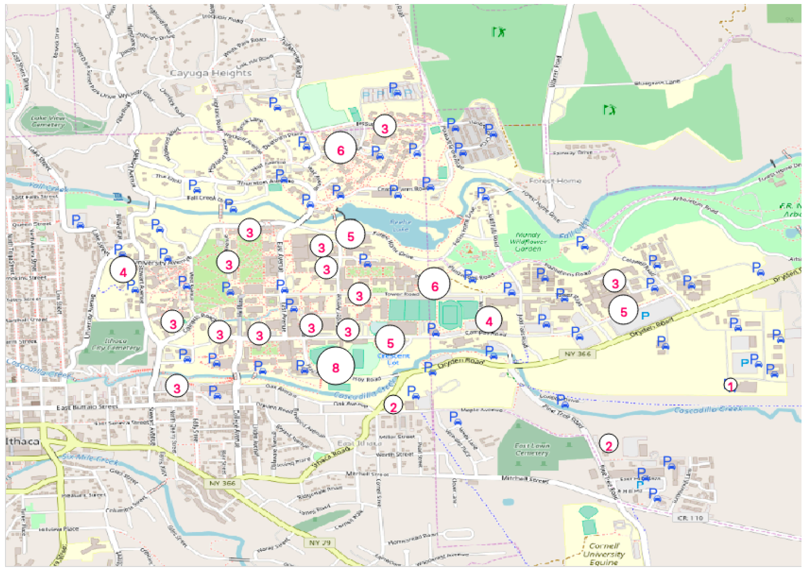


Figure 4: Installation of charging stations from the initial calculation (Basic Model)

Figure 5 visualizes the assignment of EVs from selected buildings to parking lots. Since we restrain EVs from parking lots beyond maximum acceptable walking time, the actual parking options for drivers are not as many as our presumption, which considerably reduces the complexity of solving this NP-Hard model. Furthermore, we can notice many parking lots are assigned to accommodate EVs from different selected buildings.

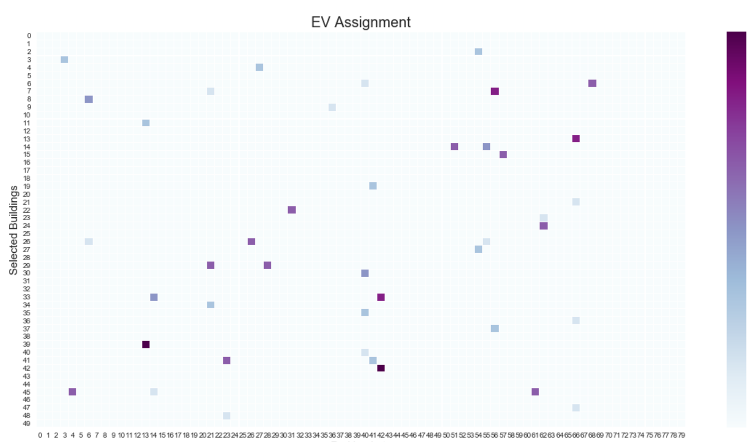


Figure 5: EV assignment from the initial calculation (Basic Model)

4.2.2 *For Expanded Model*

By running the CPLEX of our expanded model in Python (See as Source Code 3 in APPENDIX B), we prove the feasibility of our model and get credible results as detailed below:

In Table 9, all 99 EVs have been given assignments. 24 out of 80 parking lots are chosen to install charging stations, which supports our goal of controlling construction costs. 76 charging stations have been installed, while 49 are for EVs in class 6 because of its large proportion. There are no charging stations installed for EVs in class 1 or 2, since the percentages of them are so small that their parking demands have been rounded down to zero. The monetized value of environmental benefits is relatively low because the number of EVs is quite low in the initial calculation. The actual service level is 77%, which is above our designed service level 70%. This is because the current feasible region for this MIP problem is limited due to the small number of EVs.

	Initial Calculation	EV Class	Number of Charging Stations Installed (in EV classes)
Number of EVs	99	Class 1	0
Number of Assigned EVs	99	Class 2	0
Number of Chosen Parking Lots	24	Class 3	11
Total Parking Capacity for EVs	259	Class 4	20
Number of Charging Stations Installed	76	Class 5	19
Maximum Charging Stations in a Chosen Parking Lot	6	Class 6	26
Minimum Charging Stations in a Chosen Parking Lot	1	Total	76
Convenience Benefits ($)	732229		
Environmental Benefits ($)	85238		
Construction Costs ($)	414000		
Overall Benefits ($)	50089		

Table 9: Numeric results from the initial calculation (Expanded Model)

In Figure 6, parking lots chosen are illustrated by sized pie charts. The percentages of charging stations installed for different EV classes are shown as pies. We can see for different parking lots, there are different combinations of charging stations. This depends on the composition of their neighboring EV charging demands, since EVs will be given charging accommodations in the order from class 1 (if any) to class 6.

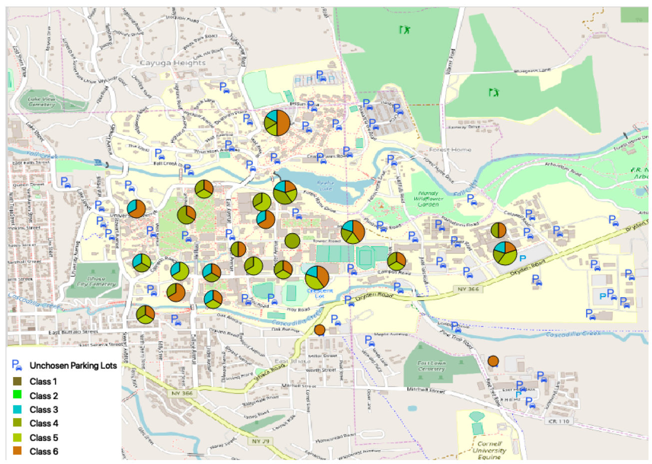


Figure 6: Installation of charging stations (Initial calculation of Expanded Model)

Figure 7 visualizes the assignment of EVs in total from selected buildings to parking lots.

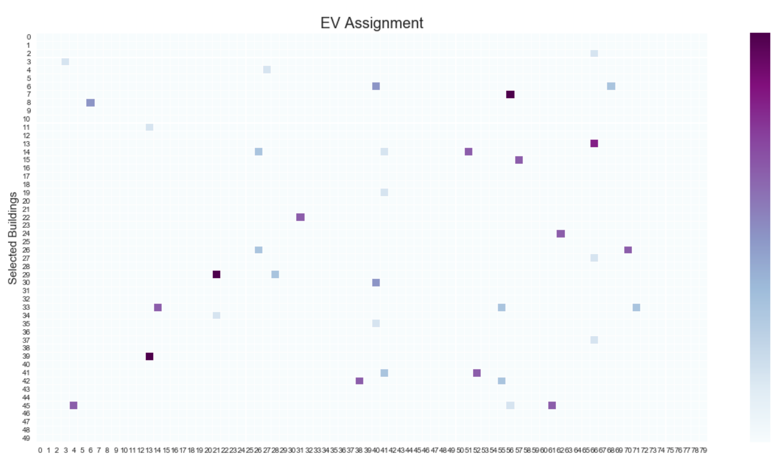


Figure 7: EV assignment from the initial calculation (Expanded Model)

4.3 Results Analysis

While the technical feasibility of our two models has been demonstrated in 4.2, it is equally important to examine the robustness of our models from different perspectives. Since the expanded model includes but not limited to many features of the basic model, it should be investigated with methods like sensitivity analysis and scenario analysis.

4.3.1 Linearized Relaxation

Linearized relaxation is a commonly used approach for NP-Hard problems. Especially in our circumstance, we would like to propose a plausible hypothesis that it does not make much difference when it comes to implementing the design from our Mixed Integer Programming (MIP) model or a Linear Programming (LP) model. Therefore, it is necessary to inspect the results of linearized relaxation of the expanded model.

In our CPLEX model, it is uncomplicated to change from MIP to LP by just setting up decisions variables as continuous variables instead of integer ones. After obtaining results, we round them off to integers. The comparisons are shown in Figure 8, 9, and 10. From Figure 8, we can tell that Linearized relaxation generates higher overall benefits, convenience benefits and construction costs, but also lower environmental benefits. By checking Figure 9 and 10, it is apparent that Linearized Relaxation chooses one more closer parking lot, which incurs more construction costs but much more convenience benefits. Moreover, it installs seven less charging stations, which decreases environmental benefits. Since linearized relaxation has a larger feasible region, it chooses to install less charging stations for EVs in class 6 because environmental benefits brought by them cannot cover the other costs they incur. After weighted combination, the overall benefits are higher than initial calculation.

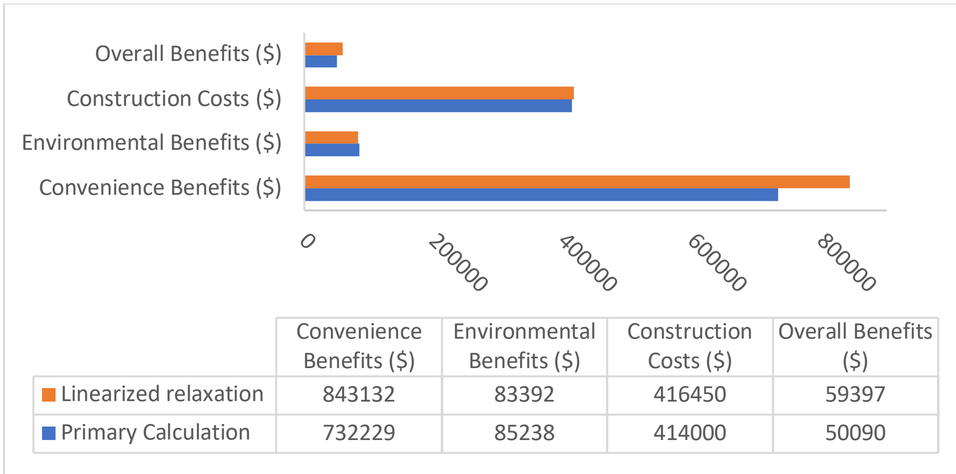
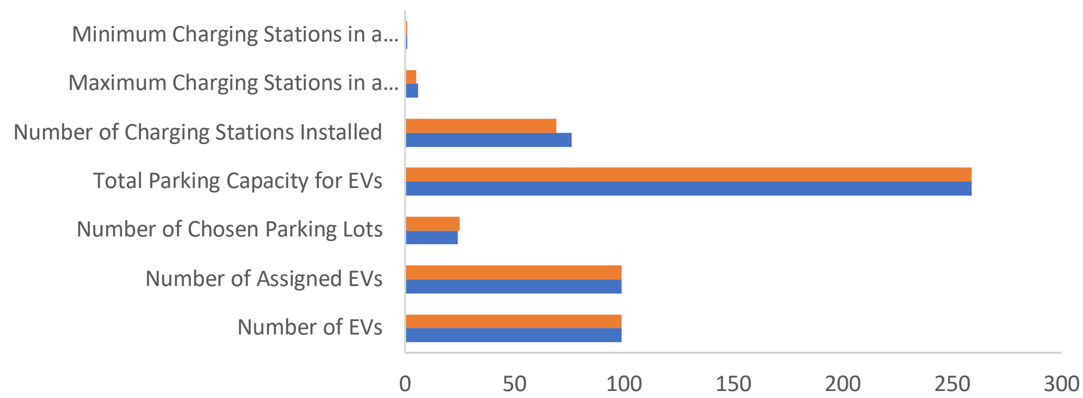


Figure 8: Comparison between the initial calculation and linearized relaxation – (1)

Figure 9: Comparison between the initial calculation and linearized relaxation – (2)



	Number of EVs	Number of Assigned EVs	Number of Chosen Parking Lots	Total Parking Capacity for EVs	Number of Charging Stations Installed	Maximum Charging Stations in a Chosen Parking Lot	Minimum Charging Stations in a Chosen Parking Lot
Linearized relaxation	99	99	25	259	69	5	1
Primary Calculation	99	99	24	259	76	6	1

Figure 10: Comparison between the initial calculation and linearized relaxation – (3)

More specifically, we would like to probe deeper into the results of decision variables from linearized relaxation and the initial calculation. The differences between result matrixes of decision variables have been calculated, and the nonzero value has been highlighted (See as Table 10, 11 and 12 in APPENDIX A). It is plain to see that the specific results of the two approaches are entirely different, which influences the final performance of the implementation. Therefore, although linearized relaxation is an acceptable approach to decrease computational complexity, it would be better to apply the mixed integer model for an optimal network design.

4.3.2 Sensitivity Analysis

Sensitivity analysis is quite critical in scientific research because it can demonstrate how the uncertainty in the model input can influence the output of the model (Saltelli, Tarantola, Campolongo, & Ratto, 2004). We decide to explore how the different weights of three sub-objectives and maximum acceptable walking time affect model results.

1. Different Weights of three sub-objectives

To better look into the effects of different weights, extreme numbers as follows have been chosen for each weight for comparisons.

- $\omega_1 = 0.8,\ \omega_2 = 0.1,\ \omega_3 = 0.1$
- $\omega_1 = 0.1,\ \omega_2 = 0.8,\ \omega_3 = 0.1$
- $\omega_1 = 0.1,\ \omega_2 = 0.1,\ \omega_3 = 0.8$

From Table 13 and Figure 11-14, it can be observed that placing greater weight in construction costs ($\omega_3 = 0.8$) indeed results in less chosen parking lots and more charging stations in one parking lot to avoid an initial grid connecting cost, although sacrificing convenience benefits. Moreover, the overall benefits are below zero, which means this project is economic infeasible if we care construction costs so much. However, if $\omega_1 = 0.8$, which means we give heavier weight on the sub-objective of minimizing walking time, more parking lots are being chosen from central campus, which are much closer to many selected buildings although having limited capacities. Moreover, if we set $\omega_2 = 0.8$, more charging stations are installed, which serve more EVs and bring more environmental benefits.

From analysis above, we can conclude that the overall benefits are sensitive to the weights of three sub-objectives, which requires us to carefully set initial weights. According to our thesis motivation and interview results, the importance ranking of three sub-objectives is Environmental Benefits > Construction Costs > Convenience Benefits, which means $\omega_1 = 0.1, \omega_2 = 0.7, \omega_3 = 0.2$ are reasonable weights.

	$\omega_1 = 0.1$ $\omega_2 = 0.7$ $\omega_3 = 0.2$	$\omega_1 = 0.8$ $\omega_2 = 0.1$ $\omega_3 = 0.1$	$\omega_1 = 0.1$ $\omega_2 = 0.8$ $\omega_3 = 0.1$	$\omega_1 = 0.1$ $\omega_2 = 0.1$ $\omega_3 = 0.8$
Number of EVs	99	99	99	99
Number of Assigned EVs	99	99	99	99
Number of Chosen Parking Lots	24	34	29	18
Total Parking Capacity for EVs	259	259	259	259
Number of Charging Stations Installed	76	83	83	75
Max. Charging Stations in a Chosen Parking Lot	6	5	6	10
Min. Charging Stations in a Chosen Parking Lot	1	1	1	1
Convenience Benefits (\$)	732229	847240	816599	471292
Environmental Benefits (\$)	85238	87168	87168	84963
Construction Costs (\$)	414000	549500	487000	337500
Overall Benefits (\$)	50090	631559	102694	-214375

Table 13: Comparison between different weights of sub-objectives

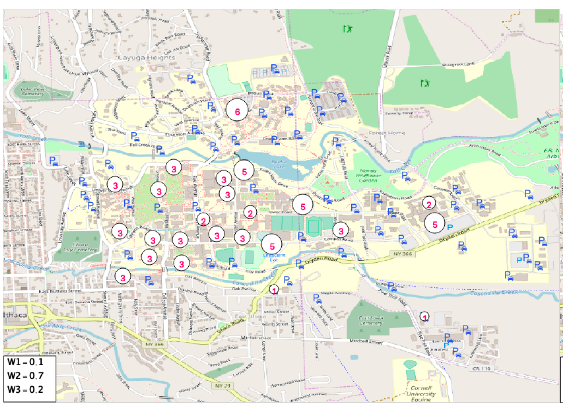


Figure 11: $\omega_1 = 0.1,\ \omega_2 = 0.7,\ \omega_3 = 0.2$

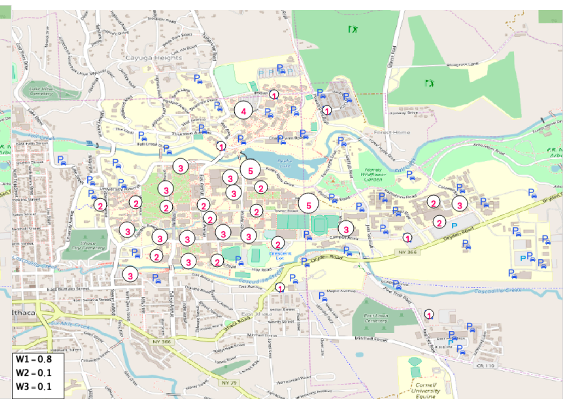


Figure 12: $\omega_1 = 0.8,\ \omega_2 = 0.1,\ \omega_3 = 0.1$

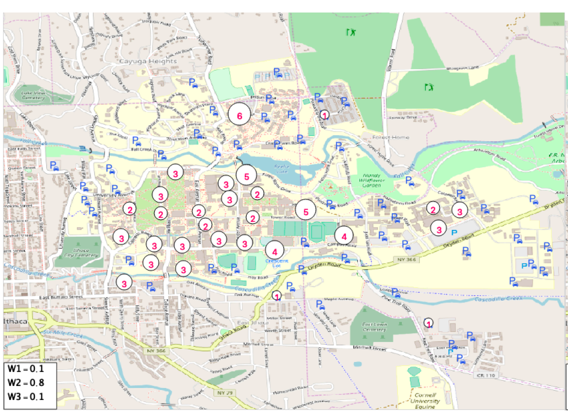


Figure 13: $\omega_1 = 0.1,\ \omega_2 = 0.8,\ \omega_3 = 0.1$

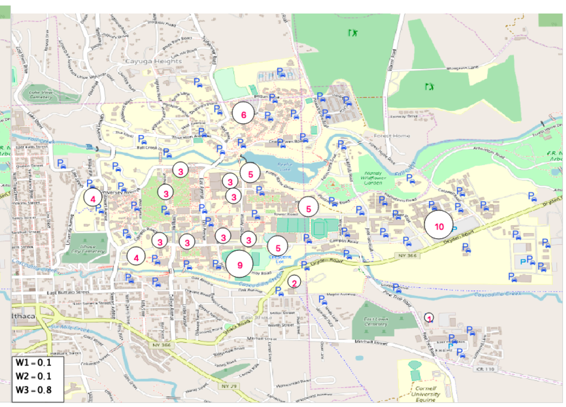


Figure 14: $\omega_1 = 0.1,\ \omega_2 = 0.1,\ \omega_3 = 0.8$

2. Different maximum acceptable walking time

Although we set maximum acceptable walking time (t^{MAX}) as 10 minutes in the initial calculation, there is also some other value used by researchers. Hence, it is essential to apply sensitivity analysis on t^{MAX} so that we can inspect whether it exerts significant influence on results. (See as follows)

- $t^{MAX} = 5\ minutes$
- $t^{MAX} = 10\ minutes$
- $t^{MAX} = 15\ minutes$
- $t^{MAX} = 20\ minutes$

In Table 14 and Figure 15-18, the numeric and design results from different t^{MAX} have been given. As for $t^{MAX} = 5\ mins$ and $t^{MAX} = 10\ mins$, the results are slightly different in that four more parking lots have been chosen to install charging stations in the previous situation. This is because of the limitation of maximum acceptable walking time, which pushes model to choose more closer parking lots to fulfill requirement of service level. However, when it comes to a larger t^{MAX}, the results are all the same because of our sub-objective to maximize convenience benefits and environmental benefits. Therefore, we can confidently determine $t^{MAX} = 10\ mins$ is an appropriate input and the results are not significantly sensitive to t^{MAX} as long as feasible solutions exist.

Moreover, we can see that the convenience benefits and environmental benefits are higher when $t^{MAX} = 5\ mins$, because it connects more closer parking lots and installs more charging stations, which also leads to higher construction costs. That's why the overall benefits are smaller than other cases.

t^{MAX}	5 mins	10 mins	15 mins	20 mins
Number of EVs	99	99	99	99
Number of Assigned EVs	99	99	99	99
Number of Chosen Parking Lots	28	24	24	24
Total Parking Capacity for EVs	259	259	259	259
Number of Charging Stations Installed	80	76	76	76
Max. Charging Stations in a Chosen Parking Lot	5	6	6	6
Min. Charging Stations in a Chosen Parking Lot	1	1	1	1
Convenience Benefits ($)	787768	732229	732229	732229
Environmental Benefits ($)	86341	85238	85238	85238
Construction Costs ($)	470000	414000	414000	414000
Overall Benefits ($)	45215	50090	50090	50090

Table 14: Comparison between different maximum acceptable walking times

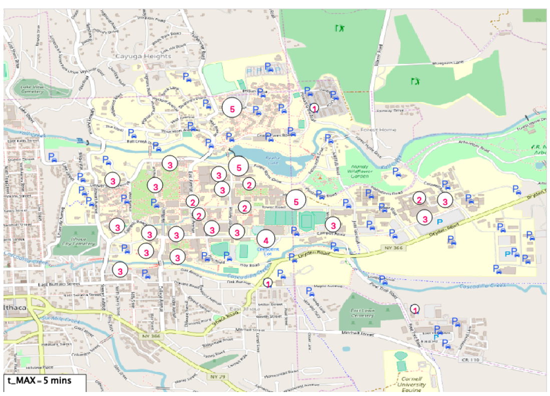


Figure 15: $t^{MAX} = 5\ minutes$

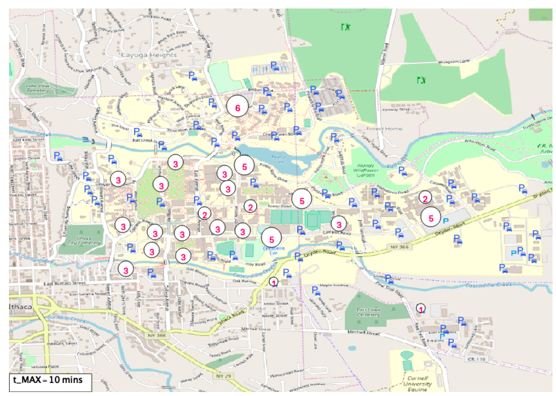


Figure 16: $t^{MAX} = 10\ minutes$

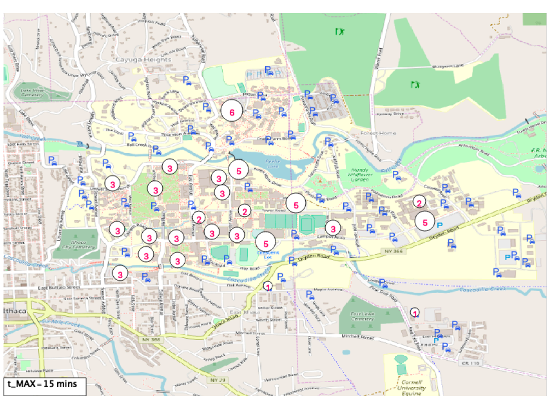


Figure 17: $t^{MAX} = 15\ minutes$

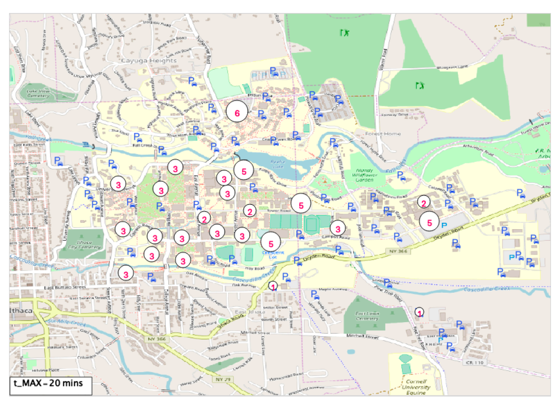


Figure 18: $t^{MAX} = 20\ minutes$

4.3.3 Scenario Analysis

Scenario analysis is vital for considering possible future development.[25] Some inputs in our models like rates of EV penetration are likely to change over time, and it would call for upgrades or adjustments in our charging station network. Thus, it is crucial to understand what our network will be like in different future scenarios.

1. Change in rates of EV penetration

With the development of battery technology and increased environmental awareness, it is not hard to imagine a mounting rate of EV penetration, which poses considerable challenges to our charging station network. Furthermore, just like we have analyzed in 4.3.2, there might be not enough parking space for increasing EVs within our assumed maximum acceptable walking time. So, before any model solving, we need to adjust t^{MAX} to a fairly larger number like 20 minutes. Subsequently, we assume different scenarios as follows:

- Rate of EV penetration = 1%
- Rate of EV penetration = 5%
- Rate of EV penetration = 10%
- Rate of EV penetration = 20%
- Rate of EV penetration = 40%

First of all, we would like to see how the charging station network will evolve with the increasing rate of EV penetration if we only equally consider environmental

[25] Wikipedia. (2019, March 8). *Scenario analysis.* Retrieved from https://en.wikipedia.org/wiki/Scenario_analysis

benefits and construction costs, which is to set $\omega_1 = 0, \omega_2 = 1,\ \omega_3 = 1$. The comparisons of results are as follows:

Rate of EV Penetration	1%	5%	10%	20%
Number of EVs	99	573	1175	2364
Number of Assigned EVs	99	573	1175	2364
Number of Chosen Parking Lots	12	20	22	23
Total Parking Capacity for EVs	259	733	1337	2521
Number of Charging Stations Installed	73	408	824	1658
Actual Service Level	74%	71%	70%	70%
Max. Charging Stations in a Chosen Parking Lot	11	54	108	217
Min. Charging Stations in a Chosen Parking Lot	4	11	17	31
Environmental Benefits ($)	84411	558739	1187124	2446209
Construction Costs ($)	259500	862000	1511000	2774500
Overall Benefits ($)	-175089	-303261	-323876	-328291

Table 15: Numeric results from the change in rates of EV penetration (1)

From Table 15, all overall benefits are negative, which means they are economic infeasible from the comparison of absolute value of environmental benefits and construction costs. However, if we look into those numbers, we can see the negative value is almost unchanged with the increasing value of environmental benefits and construction costs, which makes the overall benefits relatively smaller. Therefore, with the increasing rate of EV penetration, the gap between environmental benefits and construction costs is relatively getting smaller, which means the network is still feasible in a high rate of EV penetration considering obtaining the high environmental benefits.

Then, we would like to dig into scenarios under different rate of EV penetrations if we also include convenience benefits into consideration, which restores weights as $\omega_1 = 0.1, \omega_2 = 0.7,\ \omega_3 = 0.2$.

In Table 16, with the increasing rate of EV penetration, it is evident that numbers of parking lots connecting to grid network and corresponding installed charging stations are getting larger, as we primarily expect. More specifically, the number of chosen parking lots doubles from 1% of EV penetration to 5% of EV penetration but does not increase much from 10% of EV penetration to 40% of EV penetration. This is because the monetized value of convenience benefits overweighs construction costs when there are more EVs, and then our models tend to connect those closer parking lots to grid network in order to maximize users' total reduced walking time, instead of building more chargers in those farther parking lots already chosen. Also, we can observe that the actual service level is 77% in 1% of EV penetration but right above our expected 70% in the other scenarios. This can be explained with the results from linearized relaxation in 4.3.1. When the number of EVs is small, constraints on integer variables largely confine the feasible region, but this is not the case when it comes to a higher rate of EV penetration. Then, we can see that the convenience benefits are all positive because most EVs are given parking assignments which require shorter walking than the average walking time on campus (See as Figure 19). Moreover, there are 345 more charging stations installed from 1% of EV penetration to 5% of EV penetration and 1659 more stations installed from 20% of EV penetration to 40% of EV penetration, while the construction costs are more than doubled only in the previous scenario. This is because costs of connecting chosen parking lots to electrical grid dominate the total costs at beginning, then the relatively lower costs of installing new charging station keep mounting in the latter case. As for the environmental benefits, they are all lower than construction costs, because we only calculate the environmental benefits brought by commuting between home and campus, which is directly served by campus charging stations. However, after incorporating convenience benefits and weighted summation, the overall benefits are all above zero, which prove the economic feasibility of our network in different scenarios.

Rate of EV Penetration	1%	5%	10%	20%	40%
Number of EVs	99	573	1175	2364	4737
Number of Assigned EVs	99	573	1175	2364	4737
Number of Chosen Parking Lots	24	53	60	68	70
Total Parking Capacity for EVs	259	733	1337	2521	4899
Number of Charging Stations Installed	76	421	841	1676	3335
Actual Service Level	77%	73%	72%	71%	70%
Max. Charging Stations in a Chosen Parking Lot	6	43	86	170	339
Min. Charging Stations in a Chosen Parking Lot	1	2	3	3	3
Convenience Benefits ($)	732229	3116695	4920128	8027973	13641626
Environmental Benefits ($)	85238	562322	1191809	2451170	4948653
Construction Costs ($)	414000	1294000	2011500	3364000	5877500
Overall Benefits ($)	50090	446495	923979	1845816	3652719

Table 16: Numeric results from the change in rates of EV penetration (2)

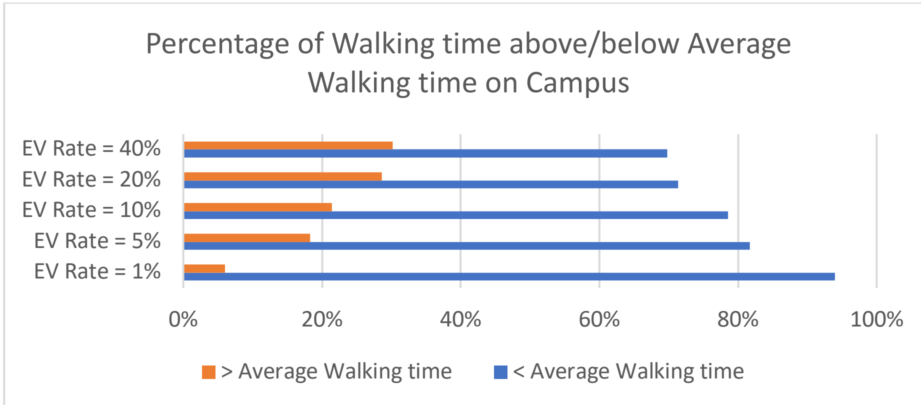
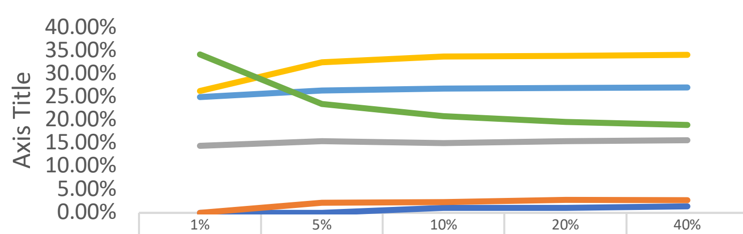


Figure 19: Percentage of Walking time above/below average walking time

From Figure 20, it can be told that the percentage of installed charging stations for EVs in class 1 is increasing even beyond its percentage in Table 6 but that for EVs in class 6 is decreasing, which proves that our sub-objective for high environmental benefits does take effect by giving higher charging priority to EVs with longer commuting distances.



	1%	5%	10%	20%	40%
Class 1	0.00%	0.00%	1.07%	1.13%	1.41%
Class 2	0.00%	2.14%	2.26%	2.80%	2.73%
Class 3	14.47%	15.44%	15.10%	15.51%	15.68%
Class 4	26.32%	32.54%	33.77%	33.89%	34.12%
Class 5	25.00%	26.37%	26.87%	27.03%	27.08%
Class 6	34.21%	23.52%	20.93%	19.63%	18.98%

Figure 20: Percentages of installed charging stations for different EV classes concerning different rates of EV penetration

In Figure 21-25, we can see that more and more parking lots in west and central campus have been connected to the grid network and used for charging. Moreover, there are six major parking lots (illustrate as blue circles) accommodating constantly increasing EVs because of their larger parking capacities. Therefore, it is vital to implement larger power transformers in those parking lots in case of potential overloading in the future.

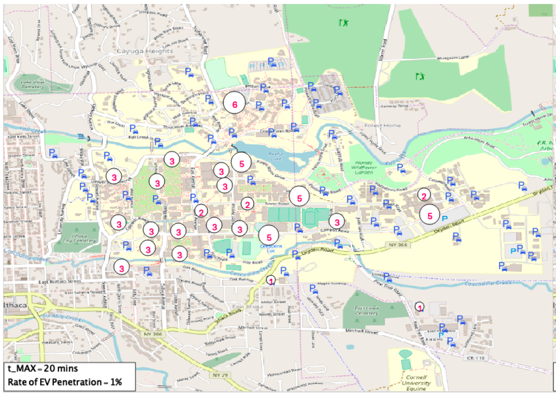


Figure 21: Rate of EV penetration = 1%

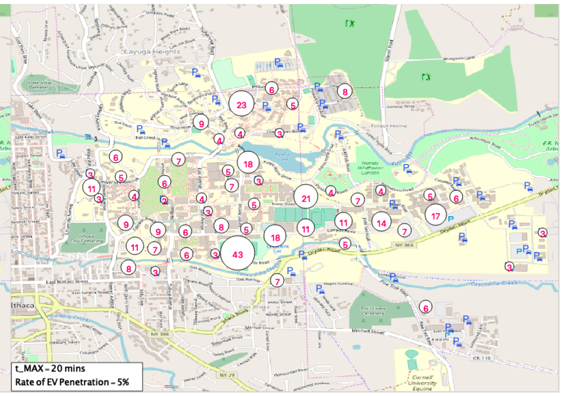


Figure 22: Rate of EV penetration = 5%

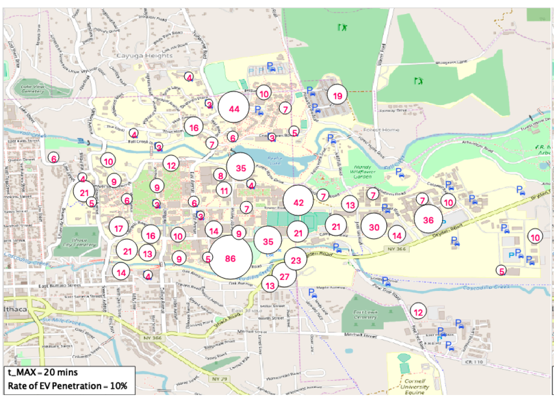


Figure 23: Rate of EV penetration = 10%

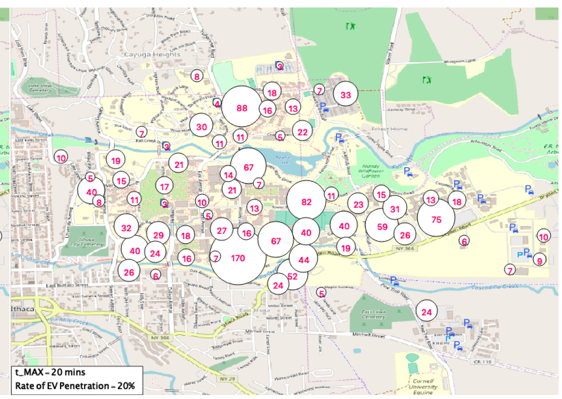


Figure 24: Rate of EV penetration = 20%

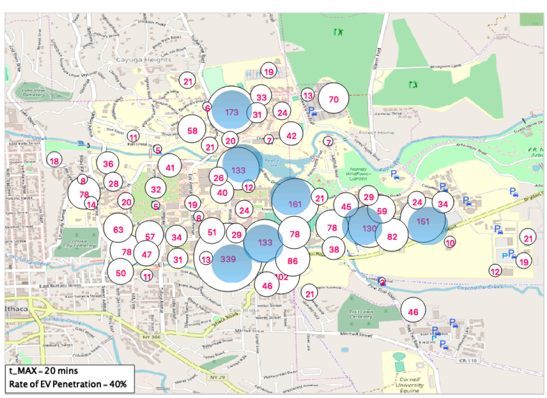


Figure 25: Rate of EV penetration = 40%

CHAPTER 5

CONCLUSION

In this thesis, first, we identify the enormous potential of Electric Vehicles (EVs) and lack of sufficient charging stations at workplaces like university campuses, which severely limits the popularization of EVs among university employees. Then, the problem of designing an optimal EV charging station network at campus has been decomposed through carefully proposed assumptions and a well-organized structure. Afterward, a basic Mixed Integer Programming (MIP) model has been selected from the literature and also expanded to demonstrate a more complicated reality. The models determine the optimal installation of charging stations and the best assignment of charging demand with objectives of minimizing construction costs, maximizing convenience benefits, and even maximizing the environmental benefits in the expanded model. Moreover, the optimization, constrained by the physical capacities of the parking lots, a guaranteed service level of the whole network, and requirements for better network management, is solved by CPLEX in Python with kinds of necessary inputs from credible literature, authoritative reports, appropriate assumptions, face-to-face interviews, and meticulous GIS extractions. The validity of the models has also been verified by linearized relaxation, sensitivity analysis, and scenario analysis. For further study, we might improve the applicability of our models by designing an effective heuristic algorithm like Tabu Search for any practical case in a greater magnitude.

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APPENDIX A

TABLES

Cluster ID	Building ID	Building Name	Net Area (ft^2)	Longitude	Latitude
0	20	UNIV AVE 600	13865	-76.4914	42.4498
0	195	STEWART AVE 640, KAHIN CENTER	12426	-76.4914	42.4480
0	196	VON CRAMM HALL	13143	-76.4913	42.4489
0	199	STEWART AVENUE 660, STEWART HS	12753	-76.4912	42.4485
1	228		44850	-76.4541	42.4468
2	151	HASBROUCK COMMUNITY CENTER	7063	-76.4719	42.4563
2	152	HASBROUCK APARTMENTS	282605	-76.4723	42.4560
3	19	E ITHACA ENVIRONMENTAL HEALTH	4895	-76.4756	42.4420
3	54	MAPLE AVE PIPE/WELDING SHOP	4692	-76.4751	42.4421
3	55	FM SHOPS ANNEX	8760	-76.4759	42.4418
3	56	MAPLE AVE 104	4078	-76.4771	42.4415
3	146	MAPLE AVE 116	5525	-76.4762	42.4416
3	147	MAPLE AVE 120	40771	-76.4759	42.4415
3	192	HUMPHREYS SERVICE BLDG	74922	-76.4756	42.4427
3	198	CENTRAL HEATING PLANT	94140	-76.4747	42.4427
3	220	CHILL WATER-PLANT 3	13666	-76.4741	42.4433
3	243	MAPLE AVE 110	4867	-76.4768	42.4413
4	6	EAST HILL PLAZA	122153	-76.4635	42.4379
4	145	PINE TREE RD 391	26258	-76.4653	42.4391
4	173	EAST HILL OFFICE BUILDING	58323	-76.4632	42.4392
5	176	TRIPHAMMER RD 310, AFRICANA CTR	18234	-76.4823	42.4574
5	177	HURLBURT HOUSE	39538	-76.4840	42.4580
6	72	NECROPSY WING	9014	-76.4652	42.4482
6	116	CLINICAL PROGRAMS - L BARN	5680	-76.4645	42.4483
6	117	CLINICAL PROGRAMS - M BARN	5358	-76.4645	42.4484
6	118	CLINICAL PROGRAMS - BREEZEWAY	8301	-76.4646	42.4481
6	119	CLINICAL PROGRAMS - SURGERY	17643	-76.4648	42.4481
6	120	CLINICAL PROGRAMS-MULTIPURPOSE	28989	-76.4651	42.4476
6	212	BASIC SCIENCE BUILDING	41914	-76.4660	42.4484
6	213	FILTER PLANT	25622	-76.4660	42.4500
6	223	WASTE MANAGEMENT FACILITY	4200	-76.4655	42.4483
6	286	NYS Veterinary Diagnostic Lab	131271	-76.4643	42.4488
6	289	MOORE LABORATORY	29228	-76.4658	42.4480
6	290	SCHURMAN HALL	35381	-76.4662	42.4481

6	291	VET RESEARCH TOWER	125507	-76.4662	42.4473
6	292	VET EDUCATION CENTER	19846	-76.4658	42.4475
6	293	CVM Center	82811	-76.4659	42.4478
7	51	COMPUTING & COMMUNICATIONS CTR	60100	-76.4790	42.4493
7	93	ROBERTS HALL	42706	-76.4794	42.4487
7	98	SAVAGE HALL	33695	-76.4801	42.4497
7	99	KINZELBERG HALL	40450	-76.4799	42.4500
7	171	BAILEY HALL ADDITION	8749	-76.4801	42.4495
7	178	Martha Van Rensselaer Hall East	28432	-76.4780	42.4501
7	193	Martha Van Rensselaer Hall West	40461	-76.4791	42.4502
7	194	Martha Van Rensselaer Hall	184545	-76.4787	42.4499
7	222	NEWMAN, FLOYD R. LABORATORY	52201	-76.4804	42.4502
7	242	CALDWELL HALL	31316	-76.4783	42.4492
7	275	BAILEY HALL	47398	-76.4801	42.4492
7	278	HUMAN ECOLOGY BUILDING	98125	-76.4785	42.4505
7	296	ST OLIN	105612	-76.4811	42.4507
8	13	SCHWARTZ CTR-PERFORMING ARTS	111530	-76.4859	42.4425
8	14	CASCADILLA HALL	98624	-76.4868	42.4425
8	161	HUGHES HALL	62324	-76.4863	42.4437
8	162	MYRON TAYLOR JANE FOSTER ADD	70442	-76.4857	42.4437
8	251	SHELDON COURT	48881	-76.4856	42.4422
9	214	LIBRARY ANNEX-STORAGE FACILITY	35957	-76.4582	42.4424
9	215	LIBRARY STORAGE FACILITY-ADDTN	53394	-76.4576	42.4425
10	25	BARTON PLACE, 109	4944	-76.4879	42.4532
10	26	THURSTON COURT APARTMENTS	12518	-76.4865	42.4535
11	2	RICE HALL	31415	-76.4741	42.4479
11	3	LITTLE RICE	2415	-76.4741	42.4481
11	10	BRUCKNER LAB	18342	-76.4741	42.4483
11	11	BEEBE HALL	14744	-76.4742	42.4489
11	52	FERNOW HALL	31053	-76.4751	42.4484
11	169	WILSON SYNCHROTRON LAB & RING	124521	-76.4741	42.4474
12	8	BLAIR FARM BARN	8312	-76.4689	42.4430
13	75	GEORGE JAMESON HALL	65999	-76.4782	42.4557
13	81	UJAMAA RESID COLL-LOW RISE #10	40629	-76.4767	42.4554
13	83	CLARA DICKSON HALL	168791	-76.4792	42.4546
13	109	NORTH CAMPUS LOW RISE #9	41302	-76.4761	42.4551
13	159	KAY HALL	29775	-76.4780	42.4541
13	160	BAUER HALL	30504	-76.4785	42.4537
13	172	COURT RESIDENCE HALL	30076	-76.4780	42.4545

13	236	MEWS RESIDENCE HALL	87129	-76.4768	42.4544
13	253	MARY DONLON HALL	133594	-76.4777	42.4550
14	36	MORRILL HALL	40611	-76.4853	42.4486
14	38	DAY HALL	87977	-76.4833	42.4472
14	39	STIMSON HALL	61439	-76.4833	42.4478
14	40	WILLARD STRAIGHT HALL	113988	-76.4856	42.4466
14	41	THE CORNELL STORE	37267	-76.4842	42.4467
14	150	JENNIE MCGRAW TOWER @ URIS LIB	5485	-76.4850	42.4476
14	163	KROCH, CARL A LIBRARY	99541	-76.4834	42.4480
14	239	URIS LIBRARY	99024	-76.4853	42.4477
14	240	SAGE CHAPEL	22201	-76.4844	42.4472
14	257	BARNES HALL	21618	-76.4843	42.4464
14	271	OLIN LIBRARY	240026	-76.4842	42.4478
15	46	TEAGLE HALL	93608	-76.4791	42.4458
15	104	GRUMMAN SQUASH COURTS	17104	-76.4798	42.4450
15	165	HOY ROAD PARKING GARAGE	289693	-76.4796	42.4440
15	166	SCHOELLKOPF PRESSBOX	7316	-76.4794	42.4441
15	209	SCHOELLKOPF MEMORIAL	40311	-76.4786	42.4450
15	217	VISITING TEAM FACILITY	8349	-76.4792	42.4450
15	229	Bill and Melinda Gates Hall	105434	-76.4810	42.4450
16	285	CORNELL CHILD CARE CENTER	17079	-76.4759	42.4594
17	126	FARM SERVICE SHOP	12965	-76.4584	42.4465
17	127	ENVIRONMENTAL HEALTH & SAFETY	9166	-76.4598	42.4464
17	128	FARM SERVICE OPEN SHED C	6389	-76.4592	42.4462
18	129	MOAKLEY HOUSE - GOLF COURSE	10160	-76.4673	42.4582
19	15	EDGEMOOR LANE 107, CHI PHI	18291	-76.4888	42.4437
19	16	SOUTH AVENUE 14	14722	-76.4880	42.4451
19	17	MARYANN WD 104, DELTA TAU DELTA	18277	-76.4890	42.4454
19	85	EDGEMOOR LANE 112	9295	-76.4885	42.4441
19	170	MARYANN WD 120, PHI KAPPA PSI	24103	-76.4894	42.4459
19	237	FOREST PARK LANE 1, SIGMA PHI	19876	-76.4886	42.4460
19	238	FOREST PARK LA 2, PSI UPSILON	23120	-76.4888	42.4465
19	247	SOUTH AVENUE 13	18168	-76.4872	42.4445
19	249	SOUTH AVENUE 6, DELTA UPSILON	20259	-76.4870	42.4452
19	280	NOYES COMMUNITY AND REC CENTER	28760	-76.4880	42.4465
20	270	Plantations Ramin Admin C	6420	-76.4719	42.4530
21	30	THURSTON AVENUE 410	11751	-76.4843	42.4539
21	31	WAIT AVENUE 302	5966	-76.4811	42.4546
21	86	WAIT AVENUE 319	4841	-76.4810	42.4537

21	87	THURSTON AVE 536	3832	-76.4813	42.4537
21	88	THURSTON AVENUE 534, ZETA PSI	14195	-76.4818	42.4541
21	89	WAIT AVENUE 308	5081	-76.4806	42.4543
21	144	ANNA COMSTOCK HOUSE	20291	-76.4825	42.4539
21	232	WAIT AVE 228, PROS OF WHITBY	7324	-76.4821	42.4549
21	235	RISLEY, PRUDENCE RESID. COLLEGE	96301	-76.4820	42.4531
22	32	FOUNDRY	11635	-76.4835	42.4515
22	33	SIBLEY HALL	86194	-76.4841	42.4509
22	34	WHITE HALL	42050	-76.4854	42.4503
22	35	MCGRAW HALL	59343	-76.4854	42.4494
22	37	RAND HALL	30379	-76.4829	42.4512
22	114	LINCOLN HALL	91253	-76.4835	42.4502
22	143	JOHNSON MUSEUM OF ART	82035	-76.4863	42.4509
22	224	MILSTEIN HALL	56025	-76.4835	42.4512
22	244	OLIVE TJADEN HALL	50567	-76.4854	42.4509
23	18	WILSON SYNCHROTRON LAB & RING	124521	-76.4731	42.4450
23	60	GRAPHIC ARTS SERVICES BLDG	12706	-76.4712	42.4434
23	107	Wilson Center Modular Unit	4085	-76.4721	42.4448
23	110	Wilson East Modular Unit	6841	-76.4718	42.4448
23	294	MACHINE LABORATORY	10126	-76.4714	42.4433
24	4	MORRISON HALL	140488	-76.4693	42.4468
24	5	Food Science Laboratory	29461	-76.4703	42.4473
24	7	RILEY-ROBB HALL	115053	-76.4712	42.4460
24	57	LIVESTOCK PAVILION	15400	-76.4707	42.4466
24	100	WING HALL WING	33148	-76.4712	42.4466
24	101	WING HALL	28084	-76.4716	42.4466
24	227	STOCKING HALL	48179	-76.4716	42.4472
24	248	STOCKING HALL ADDITION	76985	-76.4711	42.4471
24	287	STOCKING HALL EAST	40122	-76.4704	42.4471
25	90	Plntns Richard M Lewis Educ C	4312	-76.4718	42.4497
25	231	PLANTATIONS NEVIN WELCOME CTR	6239	-76.4723	42.4496
26	43	CARPENTER HALL	50577	-76.4841	42.4448
26	135	BARD HALL	50002	-76.4840	42.4439
26	164	HOLLISTER HALL	115288	-76.4846	42.4442
26	245	OLIN HALL	129897	-76.4845	42.4456
26	250	ANABEL TAYLOR HALL	53194	-76.4858	42.4449
26	265	SNEE HALL	74599	-76.4849	42.4436
26	267	MYRON TAYLOR HALL	157933	-76.4859	42.4442
26	295	Cornell Health at Gannett	101151	-76.4856	42.4457
27	69	NORTH CAMPUS TOWNHOUSE B	9587	-76.4773	42.4571

27	70	NORTH CAMPUS TOWNHOUSE C	10901	-76.4766	42.4570
27	76	ROBERT PURCELL COMMUNITY CTR	95079	-76.4775	42.4559
27	77	NORTH CAMPUS STUDENT CENTER	6878	-76.4769	42.4573
27	80	NORTH CAMPUS HIGH RISE #5	65663	-76.4768	42.4562
27	254	NORTH CAMPUS TOWNHOUSE A	24255	-76.4779	42.4572
28	23	MCGRAW PL 109, SIGMA PHI EPS	15726	-76.4888	42.4501
28	84	UNIVERSITY AVE 726, A&S	12494	-76.4888	42.4495
28	233	MCGRAW PLACE 103, WATERMARGIN	9970	-76.4882	42.4501
29	42	ILR RESEARCH	12628	-76.4801	42.4466
29	53	BIOTECHNOLOGY	173983	-76.4783	42.4465
29	58	COMSTOCK HALL-ACADEMIC II	110380	-76.4794	42.4465
29	78	DOLGEN HALL	13281	-76.4801	42.4473
29	94	KENNEDY HALL	108971	-76.4793	42.4481
29	211	MALOTT HALL	84615	-76.4802	42.4482
29	225	Academic Surge Facility A	7755	-76.4783	42.4483
29	226	Academic Surge Facility B	7920	-76.4783	42.4481
29	258	ILR CONFERENCE CENTER	30466	-76.4801	42.4469
29	262	BIOLOGICAL SCIENCE ATRIUM	28042	-76.4786	42.4472
29	263	SEELEY G MUDD BIO SCIENCE WING	53303	-76.4790	42.4472
29	264	DALE R CORSON BIO SCIENCE WING	50462	-76.4783	42.4473
29	282	WEILL HALL	279840	-76.4774	42.4468
30	1	VET CENTER FOR MOBILITY	8228	-76.4636	42.4480
30	71	Vet Annex West	2509	-76.4631	42.4481
30	91	LARGE ANIMAL ISOLATION	3925	-76.4627	42.4476
30	115	CLINICAL PROGRAMS - AMBULATORY	5529	-76.4643	42.4480
30	266	CLINICAL PROGRAMS - ARENA	7128	-76.4642	42.4479
30	283	VET MEDICAL CENTER	322940	-76.4645	42.4473
30	288	FEED STORAGE S	11139	-76.4638	42.4482
30	297	Community Practice Service Building	12000	-76.4624	42.4477
31	123	CAMPUS STORE WHSE	16120	-76.4560	42.4442
31	130	Cornell Recycle Center	14130	-76.4560	42.4433
31	131	FM SHEETMETAL/MASON SHOP	17564	-76.4560	42.4437
32	157	POMOLOGY COLD STORAGE SALES	16767	-76.4623	42.4449
33	45	URIS HALL	187041	-76.4822	42.4472
33	59	IVES HALL EAST	46981	-76.4807	42.4469
33	95	IVES HALL	110605	-76.4810	42.4473
33	96	IVES HALL WEST	10775	-76.4814	42.4470
33	136	STATLER HOTEL	150294	-76.4822	42.4464
33	158	IVES HALL FACULTY WING	55260	-76.4813	42.4467

33	206	STATLER HALL & AUDITORIUM	199037	-76.4821	42.4457
33	276	BARTON HALL	155177	-76.4807	42.4460
33	277	SAGE HALL	150716	-76.4832	42.4459
34	105	FRIEDMAN STRENGTH & CONDTN CTR	11265	-76.4758	42.4455
34	113	FRIEDMAN WRESTLING CENTER	16351	-76.4745	42.4456
34	200	BARTELS HALL	151900	-76.4763	42.4458
34	201	WILSON LAB G-LINE ADDITION	4473	-76.4741	42.4449
34	210	LYNAH RINK	68693	-76.4775	42.4457
35	9	TEACHING & RESEARCH BARN	14376	-76.4673	42.4449
35	68	BOYCE THOMPSON INSTITUTE	116854	-76.4676	42.4470
35	97	Ruminant Nutrition Laboratory	10282	-76.4675	42.4461
35	121	Lg Animal Rsch Teaching Unit	7476	-76.4675	42.4463
35	132	Federal Nematode Lb and Gh	3638	-76.4682	42.4472
35	284	EAST CAMPUS RESEARCH FACILITY	82686	-76.4659	42.4468
36	64	NORTH CAMPUS TOWNHOUSE D	10682	-76.4763	42.4572
36	65	NORTH CAMPUS TOWNHOUSE G	10913	-76.4753	42.4570
36	66	NORTH CAMPUS TOWNHOUSE F	11918	-76.4757	42.4573
36	67	NORTH CAMPUS TOWNHOUSE H	15687	-76.4749	42.4572
36	79	NORTH CAMPUS LOW RISE #7	41236	-76.4754	42.4562
36	252	NORTH CAMPUS TOWNHOUSE E	11012	-76.4760	42.4570
36	255	INTERNATL LIVING - LOW RISE #8	40451	-76.4759	42.4557
36	256	NORTH CAMPUS LOW RISE #6	40492	-76.4761	42.4563
37	49	CHILL WATER PLANT 1-WEINHOLD	10874	-76.4792	42.4513
37	50	TOBOGGAN LODGE	2245	-76.4786	42.4512
37	62	NOYES LODGE - BEEBE LAKE	9111	-76.4803	42.4521
37	63	THURSTON AVE 626, ALUMNI HOUSE	8770	-76.4809	42.4518
37	73	BALCH HALL	166814	-76.4797	42.4534
38	29	TRIPHAMMER RD 150, COOP	8162	-76.4815	42.4560
38	74	TRIPHAMMER RD 124, PI DELTA PSI	7161	-76.4814	42.4557
38	82	SISSON PLACE 10, SIGMA ALPHA MU	13244	-76.4797	42.4554
38	156	DEARBORN PLACE 208, WARI COOP	4812	-76.4825	42.4564
38	246	AMERICAN INDIAN PROGRAM HOUSE	11524	-76.4805	42.4561
39	92	WARREN HALL	130794	-76.4771	42.4492
39	106	MANN LIBRARY	136817	-76.4764	42.4488
39	111	TOWER RD WEST PURPLE GH 1023H	10150	-76.4764	42.4479
39	112	MANN LIBRARY ADDITION	111360	-76.4759	42.4489
39	153	PLANT SCIENCE BUILDING	171008	-76.4769	42.4483
39	174	BRADFIELD HALL	160673	-76.4758	42.4479
39	259	EMERSON HALL	57618	-76.4758	42.4483

40	133	CALS SURGE FACILITY	9283	-76.4684	42.4473
40	148	Plantations Horticultural C	5341	-76.4674	42.4500
40	179	PLANT VIROLOGY-NEMATOLOGY	8678	-76.4683	42.4480
40	180	Tower R East Yellow Gh 1060D	9844	-76.4683	42.4487
40	181	Tower R East Yellow Gh 1060A	4817	-76.4682	42.4483
40	182	Dimock Env Control Lb	10370	-76.4683	42.4485
40	183	Kenneth Post Laboratory	9552	-76.4690	42.4477
40	184	Tower R East Green Gh 1045B	8628	-76.4690	42.4480
40	185	Tower R East Green Gh 1045M	6535	-76.4689	42.4482
40	186	Tower R East Green Gh 1045P	6810	-76.4689	42.4483
40	187	Tower R East Green Gh 1134A	7367	-76.4689	42.4490
40	188	Tower R East Green Hdhs 1045G	10919	-76.4689	42.4487
40	189	Tower R E Blue Insectary Old	6476	-76.4695	42.4487
40	190	Tower R East Blue Gh 1061C	5807	-76.4695	42.4483
40	191	Tower R East Blue Insect-New	9312	-76.4695	42.4481
41	21	FOUNDERS HALL	19984	-76.4880	42.4484
41	22	BAKER SOUTH	18945	-76.4884	42.4485
41	24	BAKER NORTH	18918	-76.4887	42.4487
41	137	BOLDT HALL	16448	-76.4887	42.4490
41	138	BOLDT TOWER	5527	-76.4891	42.4490
41	139	MENNEN HALL	12062	-76.4881	42.4480
41	140	LYON HALL	21168	-76.4880	42.4478
41	141	WAR MEMORIAL	4082	-76.4879	42.4475
41	204	CARL BECKER HOUSE	169290	-76.4896	42.4485
41	205	CARL BECKER HOUSE	169290	-76.4895	42.4482
41	207	FLORA ROSE HOUSE	83141	-76.4888	42.4479
41	208	HANS BETHE HOUSE	142901	-76.4886	42.4470
41	219	MCFADDIN HALL	23081	-76.4880	42.4473
41	260	ALICE H. COOK HOUSE	78438	-76.4897	42.4489
41	268	BAKER TOWER	31355	-76.4881	42.4489
42	44	WARD CENTER	25251	-76.4830	42.4434
42	102	KIMBALL HALL	30280	-76.4832	42.4439
42	134	THURSTON HALL	53956	-76.4837	42.4439
42	218	FRANK H T RHODES HALL	214241	-76.4815	42.4434
42	261	GRUMMAN HALL	16289	-76.4821	42.4434
42	273	PHILLIPS HALL	99774	-76.4821	42.4446
42	274	UPSON HALL	168200	-76.4823	42.4439
42	279	DUFFIELD HALL	149762	-76.4826	42.4446
43	27	MCGRAW PLACE 118-THE OAKS	22181	-76.4893	42.4515
43	28	MCGRAW PL 122	21605	-76.4903	42.4514

44	197	SCHOELLKOPF CRESCENT	19619	-76.4778	42.4441
44	230	Fischell Band Center	4625	-76.4772	42.4438
45	12	KLARMAN HALL	72238	-76.4831	42.4491
45	47	A D WHITE HOUSE	23232	-76.4819	42.4482
45	48	SPACE SCIENCES	56966	-76.4811	42.4489
45	61	BIG RED BARN	4773	-76.4810	42.4485
45	103	ROCKEFELLER HALL	124289	-76.4818	42.4491
45	142	BAKER LABORATORY	233371	-76.4818	42.4505
45	149	CLARK HALL	243072	-76.4811	42.4497
45	221	MICRO-KELVIN	4456	-76.4812	42.4492
45	234	GOLDWIN SMITH HALL	126163	-76.4834	42.4491
45	272	PHYSICAL SCIENCES BUILDING	204029	-76.4817	42.4499
46	269	Resource Ecology & Mgt Lb	9773	-76.4669	42.4417
47	122	ROBERT J & HELEN APPEL COMMONS	62197	-76.4761	42.4536
47	216	FUERTES OBSERVATORY	4330	-76.4745	42.4528
47	241	HELEN NEWMAN HALL	76153	-76.4774	42.4530
48	154	NY, TOMPKS, ITH,115 LLENROC CT	5031	-76.4912	42.4476
48	155	NY, TMPK, STWRT AVE 618	7102	-76.4906	42.4469
48	167	NY, TMPKN, ITH,636 STWT	6270	-76.4906	42.4475
48	168	NY, TMPKN, ITH, 638 STWT	5777	-76.4906	42.4476
48	175	LLENROC COURT 101 DIOCESE	2712	-76.4908	42.4463
48	202	NY, TOMPKS, ITH,109 LLENROC CT	4047	-76.4910	42.4470
48	203	NY, TOMPKS, ITH,107 LLENROC CT	3931	-76.4910	42.4468
48	281	WILLIAM T. KEETON HOUSE	136522	-76.4896	42.4467
49	108	FS CARPENTER & PAINT SHOPS	16416	-76.4573	42.4450
49	124	East Campus Service Center	14863	-76.4561	42.4453
49	125	GROUNDS OPERATIONS FACILITY	16125	-76.4573	42.4459

Table 1: Clusters and net area of all buildings on Cornell University's campus

Cluster ID	Longitude	Latitude	Net Area (ft^2)	Cluster ID	Longitude	Latitude	Net Area (ft^2)
0	-76.4913	42.4488	52187	25	-76.4721	42.4496	10551
1	-76.4541	42.4468	44850	26	-76.4849	42.4446	732641
2	-76.4721	42.4562	289668	27	-76.4772	42.4568	212363
3	-76.4757	42.4421	256316	28	-76.4886	42.4499	38190
4	-76.4640	42.4387	206734	29	-76.4790	42.4473	961646
5	-76.4831	42.4577	57772	30	-76.4636	42.4478	373398
6	-76.4654	42.4482	570765	31	-76.4560	42.4438	47814
7	-76.4795	42.4498	773790	32	-76.4623	42.4449	16767
8	-76.4861	42.4429	391801	33	-76.4816	42.4466	1065886

9	-76.4579	42.4425	89351	34	-76.4756	42.4455	252682
10	-76.4872	42.4534	17462	35	-76.4673	42.4464	235312
11	-76.4743	42.4482	222490	36	-76.4757	42.4567	182391
12	-76.4689	42.4430	8312	37	-76.4797	42.4520	197814
13	-76.4777	42.4547	627799	38	-76.4811	42.4559	44903
14	-76.4844	42.4474	829177	39	-76.4763	42.4485	778420
15	-76.4795	42.4448	561815	40	-76.4687	42.4484	119739
16	-76.4759	42.4594	17079	41	-76.4886	42.4482	814630
17	-76.4591	42.4464	28520	42	-76.4826	42.4439	757753
18	-76.4673	42.4582	10160	43	-76.4898	42.4515	43786
19	-76.4883	42.4453	194871	44	-76.4775	42.4440	24244
20	-76.4719	42.4530	6420	45	-76.4818	42.4492	1092589
21	-76.4818	42.4540	169582	46	-76.4669	42.4417	9773
22	-76.4844	42.4507	509481	47	-76.4760	42.4531	142680
23	-76.4719	42.4442	158279	48	-76.4907	42.4471	171392
24	-76.4708	42.4468	526920	49	-76.4569	42.4454	47404

Table 2: Geographical coordinates and net area of selected buildings on campus

Cluster ID	Longitude	Latitude	Capacity	Cluster ID	Longitude	Latitude	Capacity
0	-76.4562	42.4435	136	40	-76.4643	42.4467	1117
1	-76.4937	42.4515	42	41	-76.4886	42.4461	157
2	-76.4714	42.4565	328	42	-76.4799	42.4437	872
3	-76.4767	42.4416	113	43	-76.4607	42.4483	81
4	-76.4806	42.4502	62	44	-76.4704	42.4479	111
5	-76.4676	42.4476	148	45	-76.4559	42.4453	158
6	-76.4884	42.4426	124	46	-76.4797	42.4532	46
7	-76.4625	42.4368	63	47	-76.4782	42.4494	26
8	-76.4831	42.4579	84	48	-76.4725	42.4486	49
9	-76.4570	42.4490	10	49	-76.4745	42.4457	196
10	-76.4675	42.4418	13	50	-76.4685	42.4462	332
11	-76.4880	42.4482	46	51	-76.4856	42.4493	77
12	-76.4874	42.4534	24	52	-76.4890	42.4497	68
13	-76.4745	42.4481	412	53	-76.4747	42.4436	216
14	-76.4811	42.4459	127	54	-76.4772	42.4567	81
15	-76.4775	42.4553	74	55	-76.4840	42.4454	82
16	-76.4621	42.4450	27	56	-76.4790	42.4508	339
17	-76.4766	42.4587	733	57	-76.4792	42.4457	71
18	-76.4626	42.4494	79	58	-76.4815	42.4558	10
19	-76.4714	42.4445	173	59	-76.4908	42.4480	32

20	-76.4718	42.4530	12	60	-76.4686	42.4487	69
21	-76.4769	42.4451	339	61	-76.4803	42.4490	98
22	-76.4827	42.4540	144	62	-76.4715	42.4462	197
23	-76.4913	42.4489	196	63	-76.4748	42.4536	104
24	-76.4582	42.4460	335	64	-76.4880	42.4443	197
25	-76.4665	42.4504	44	65	-76.4731	42.4555	39
26	-76.4861	42.4455	141	66	-76.4796	42.4555	443
27	-76.4651	42.4395	294	67	-76.4571	42.4440	376
28	-76.4786	42.4476	56	68	-76.4647	42.4483	57
29	-76.4733	42.4409	48	69	-76.4632	42.4379	549
30	-76.4894	42.4513	88	70	-76.4864	42.4441	116
31	-76.4845	42.4511	100	71	-76.4822	42.4470	15
32	-76.4827	42.4480	43	72	-76.4813	42.4527	48
33	-76.4863	42.4423	22	73	-76.4855	42.4524	7
34	-76.4766	42.4532	13	74	-76.4856	42.4479	7
35	-76.4618	42.4385	119	75	-76.4915	42.4500	16
36	-76.4585	42.4427	27	76	-76.4816	42.4437	28
37	-76.4667	42.4455	422	77	-76.4756	42.4423	258
38	-76.4839	42.4437	75	78	-76.4735	42.4568	28
39	-76.4755	42.4554	57	79	-76.4627	42.4481	82

Table 3: Geographical coordinates and capacities of parking lot clusters

Commuting Distance	Percent
Less than 5 miles	43.30%
5 to 9 miles	18.50%
10 to 14 miles	14.90%
15 to 19 miles	9.30%
20 to 29 miles	7.40%
30 to 39 miles	3.80%
40 to 49 miles	1.30%
50 to 59 miles	0.80%
60 or more miles	0.70%

Table 5: Distribution of employees' commuting distances at Cornell University

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
0	48	5	31	27	18	30	16	47	26	46	36	7	13	24	16	24	40	31	42	33	29	23
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35	7	20	25	23	26	15	9	22	21	19	25	30	23	30	18	16	25	8
36	23	7	25	4	4	31	26	40	23	18	9	13	17	23	23	30	3	23
37	17	9	18	13	8	35	29	37	16	11	3	9	11	17	16	21	14	28
38	23	9	21	11	3	38	33	43	20	15	5	8	14	18	19	27	10	30
39	7	16	17	18	18	26	20	28	14	8	11	16	10	18	11	14	20	19
40	5	16	24	18	21	18	12	23	21	15	20	25	18	26	17	17	20	11
41	23	21	7	25	20	42	35	40	8	10	14	13	5	5	14	22	26	35
42	16	22	7	26	21	33	29	28	5	6	14	17	8	15	6	10	27	28
43	26	23	13	27	22	45	39	45	14	14	16	13	9	6	19	27	28	38
44	8	24	14	26	23	27	21	24	11	8	16	20	12	20	7	5	28	20
45	14	18	15	21	17	33	26	34	13	6	10	13	7	15	10	16	22	26
46	13	26	28	28	31	23	20	13	25	22	30	34	27	34	22	13	31	19
47	18	4	21	6	6	33	28	36	19	14	5	11	13	20	19	26	8	25
48	26	25	8	29	24	45	39	41	9	13	18	15	10	6	17	25	30	38
49	18	29	35	26	32	2	11	29	32	29	34	39	32	40	28	23	28	8

Table 4: Matrix of walking time from selected buildings to parking lots

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-2	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-6	0	0	0	0	0	0	1	0	0	0	3	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-4	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	1	0	0	0	0	0	0	0	0	0	0	-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 10: Difference in *A*

1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	1
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	-1
23	0
24	0
25	0
26	0
27	0
28	0
29	0
30	0
31	0
32	0
33	1
34	0
35	0
36	0
37	0
38	0
39	0
40	0
41	0
42	0
43	0
44	0
45	0
46	0
47	0
48	1
49	0
50	0
51	0
52	0
53	-1
54	0
55	0
56	0
57	0
58	0
59	0
60	0
61	0
62	0
63	0
64	0
65	0
66	0
67	0
68	0
69	0
70	0
71	-1
72	0
73	0
74	0
75	1
76	0
77	0
78	0
79	0
80	0

Table 11: Difference in *I*

	1	2	3	4	5	6	Total
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	1	1	-2	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	-1	-1
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	2	2
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	1	-1	0	0	0
16	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0
22	0	0	-1	0	-2	-2	-5
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0
27	0	0	-1	0	-1	2	0
28	0	0	0	0	0	0	0
29	0	0	0	-1	0	1	0
30	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0
33	0	0	0	0	2	0	2
34	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0
39	0	0	0	1	0	-1	0
40	0	0	0	0	0	0	0
41	0	0	0	0	0	-1	-1
42	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0
48	0	0	1	1	0	0	2
49	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0
53	0	0	-1	0	0	-2	-3
54	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0
57	0	0	0	-1	0	1	0
58	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0
62	0	0	-1	0	2	-1	0
63	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0
67	0	0	0	0	0	-1	-1
68	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0
71	0	0	0	-1	0	-2	-3
72	0	0	0	1	0	-1	0
73	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0
75	0	0	1	0	1	0	2
76	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0
79	0	0	0	0	0	0	0
80	0	0	0	0	0	0	0

Table 12: Difference in *X*

APPENDIX B

SOURCE CODE

Source Code 1: Calculation of walking time matrix

```
# ** Import necessary packages **
import numpy as np
import pandas as pd
import googlemaps

# ** Read the info of parking lots and building data **
df_parking_lot = pd.read_csv('Parking lot data.csv')
df_building = pd.read_csv('Building data.csv')

# ** Set up the API key **
key = 'Put your API key here'
gmap = googlemaps.Client(key=key)

# ** Request for distance/time calculation from Google Maps API and Iterate over the JSON results **
N_b = len(df_building)
N_l = len(df_parking_lot)
distance_matrix = np.zeros((N_b, N_l))
time_matrix = np.zeros((N_b, N_l))
for i1, row1 in df_building.iterrows():
    longitude_o = row1['Longitude']
    latitude_o = row1['Latitude']
    o = (latitude_o,longitude_o)
    for i2, row2 in df_parking_lot.iterrows():
        longitude_d = row2['Longitude']
        latitude_d = row2['Latitude']
        d = (latitude_d, longitude_d)
        distance_matrix[i1, i2] = gmap.distance_matrix(o, d,
mode='walking')["rows"][0]["elements"][0]["distance"]["value"]
        time_matrix[i1, i2] = gmap.distance_matrix(o, d,
mode='walking')["rows"][0]["elements"][0]["duration"]["value"]/60

# ** Output **
df_distance=pd.DataFrame(distance_matrix)
df_distance.to_csv('walking_distance.csv')
df_time=pd.DataFrame(time_matrix)
df_time.to_csv('walking_time.csv')
```

Source Code 2: Model solving of basic model

```
# ** Import necessary packages **
import csv
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from math import radians, cos, sin, asin, sqrt
import math
import sys
import os
try:
    import docplex.mp
except:
    if hasattr(sys, 'real_prefix'):
        get_ipython().system('pip install docplex')
    else:
        get_ipython().system('pip install --user docplex')
import docplex.mp.model as cpx

# ** Read the info of parking lots **
with open('Parking lot data.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
parking_lots = data_a[1:,:].astype(float)

# ** Read the info of buildings **
with open('Building data.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
building = data_a[1:,:].astype(float)

# ** Read the matrix of walking time **
with open('walking_time.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
t = data_a[1:,1:].astype(float)

# ** Input parameters  **
# Parking Demand
N_B = len(building)
nums_parking_permits = 11840
# Parking Supply
N_L = len(parking_lots)
# Construction Costs
C_G=12500
C_S=1500
#Convenience Benefits
t_mean = 6
t_MAX = 10
M = 29.5/60
O = 2400
F = 2
#Assumed parameters
rho=0.70
w1=0.2
w2=0.8
EV_Penetration = 0.01
```

```
# ** Create indication matrix for building-parking lot pairs whose walking time is greater than the maximum acceptable walking time **
t_indicator = (t > t_MAX).astype(int)

# ** Create the vector of parking lot capacity **
q0 = parking_lots[:,3]
# ** Calculate the vector of total vehicle demand associated with each building**
P0 = np.round(nums_parking_permits*building[:,3]/sum(building[:,3]))

# ** Calculate the vector of EV parking demand associated with each building**
P = np.round(P0*EV_Penetration)

# ** Adjust the Parking Capacity vector in order to decrease the difficulty of solving**
scale_smaller_factor = sum(P)/sum(q0)
q = np.round(q0*scale_smaller_factor)+2

# ** Use Cplex to Solve this model**
Set_L = range(N_L)
Set_B = range(N_B)
mip = cpx.Model(name='Cornell_Charging_Station_Network_Basic_Model')
#Set up decision variables
I = [l for l in Set_L]
X = [l for l in Set_L]
A = [(b,l) for b in Set_B for l in Set_L]
I_vars  = mip.binary_var_dict(I, name = "I")
X_vars  = mip.integer_var_dict(X, lb = 0, name = "X")
A_vars  = mip.integer_var_dict(A, lb = 0, name = "A")
#Set up constraints
mip.add_constraints(X_vars[l]<=q[l]*I_vars[l] for l in Set_L)
mip.add_constraints(mip.sum(rho*A_vars[b,l] for b in Set_B)<=X_vars[l] for l in Set_L)
mip.add_constraints(mip.sum(A_vars[b,l] for l in Set_L) == P[b] for b in Set_B)
mip.add_constraints(A_vars[b,l] == 0 for b in Set_B for l in Set_L if t_indicator[b,l] == 1)
#Set up objectives
objective = mip.sum(w1*M*O*F*mip.sum((t_mean-t[b,l])*A_vars[b,l] for b in Set_B)
                -w2*(C_S*X_vars[l]+C_G*I_vars[l]) for l in Set_L)
mip.maximize(objective)
solution = mip.solve()
N_EV = sum(P)
N_AEV = sum(solution.get_value(A_vars[b,l]) for b in Set_B for l in Set_L)
N_CPL = sum(solution.get_value(I_vars[l]) for l in Set_L)
TPCfEV = sum(q)
N_CSI = sum(solution.get_value(X_vars[l]) for l in Set_L)
MAX_CSI = max(solution.get_value(X_vars[l]) for l in Set_L)
X_array = np.asarray(solution.get_values(X_vars[l] for l in Set_L))
MIN_CSI = np.min(X_array[np.nonzero(X_array)])
objective_value = solution.objective_value
construction_cost = sum(C_S*solution.get_value(X_vars[l])+C_G*solution.get_value(I_vars[l]) for l in Set_L)
convenience_of_users = sum(M*O*F*(t_mean-t[b,l])*solution.get_value(A_vars[b,l]) for b in Set_B for l in Set_L)
final_value_list = [N_EV,N_AEV,N_CPL,TPCfEV,N_CSI,MAX_CSI,MIN_CSI, convenience_of_users, construction_cost,objective_value]

# ** Output **
path = 'Output/(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+')'
if not os.path.exists(path):
   os.mkdir(path)

list_I = solution.get_values([I_vars[l] for l in Set_L])
df=pd.DataFrame(list_I)
```

```
df.to_csv(os.path.join(path,r'I___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetrati
on)+')_(tMAX_'+str(t_MAX)+').csv'))

list_X = solution.get_values([X_vars[l] for l in Set_L])
df=pd.DataFrame(list_X)
df.to_csv(os.path.join(path,r'X___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetrat
ion)+')_(tMAX_'+str(t_MAX)+').csv'))

list_A = solution.get_values([A_vars[b,l] for b in Set_B for l in Set_L])
array_A = np.array(list_A).reshape(N_B,N_L)
df=pd.DataFrame(array_A)
df.to_csv(os.path.join(path,r'A___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetrat
ion)+')_(tMAX_'+str(t_MAX)+').csv'))

df_P=pd.DataFrame(P)
df_P.to_csv(os.path.join(path,r'P___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetr
ation)+')_(tMAX_'+str(t_MAX)+').csv'))

df_q=pd.DataFrame(q)
df_q.to_csv(os.path.join(path,r'q___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetr
ation)+')_(tMAX_'+str(t_MAX)+').csv'))

df_fv=pd.DataFrame(final_value_list)
df_fv.to_csv(os.path.join(path,r'fv___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Pene
tration)+')_(tMAX_'+str(t_MAX)+').csv'))

# ** Draw heatmap **
plt.figure(figsize=(20,10))
sns.heatmap(array_A,cmap="BuPu", linewidth=0.05)
plt.title('EV Assignment', fontsize=20)
plt.xlabel('Parking Lots', fontsize=15)
plt.ylabel('Selected Buildings', fontsize=15)
plt.savefig(os.path.join(path,r'Heat
map___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetration)+')_(tMAX_'+str(t_M
AX)+').png'))
plt.show()
```

Source Code 3: Model solving of expanded model

```
# ** Import necessary packages **
import csv
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from math import radians, cos, sin, asin, sqrt
import math
import sys
import os
try:
    import docplex.mp
except:
    if hasattr(sys, 'real_prefix'):
        #we are in a virtual env.
        get_ipython().system('pip install docplex')
    else:
        get_ipython().system('pip install --user docplex')
import docplex.mp.model as cpx

# ** Read the info of parking lots **
with open('Parking lot data.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
parking_lots = data_a[1:,:].astype(float)

# ** Read the info of buildings **
with open('Building data.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
building = data_a[1:,:].astype(float)

# ** Read the matrix of walking time **
with open('walking_time.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
t = data_a[1:,1:].astype(float)

# ** Read the reduced carbon emissions by class **
with open('Reduced Carbon Emission.csv', newline='') as csvfile:
    data = list(csv.reader(csvfile))
    data_a = np.asarray(data)
R = data_a[1:,:].astype(float)
R[:,2] = R[:,2]/1000000

# ** Input parameters  **
# Parking Demand
N_B = len(building)
nums_parking_permits = 11840
# Parking Supply
N_L = len(parking_lots)
# Construction Costs
C_G=12500
C_S=1500
#Convenience Benefits
t_mean = 6
t_MAX = 10
M = 29.5/60
```

```python
O = 2400
F = 2
#Environmental Benefits
N_C = len(R)
S = 220
r = 1
#Assumed parameters
rho=0.70
w1=0.1
w2=0.7
w3=0.2
EV_Penetration = 0.01

# ** Create indication matrix for building-parking lot pairs whose walking time is greater than the maximum acceptable walking time **
t_indicator = (t > t_MAX).astype(int)

# ** Create the vector of parking lot capacity **
q0 = parking_lots[:,3]

# ** Calculate the vector of total vehicle demand associated with each building**
P0 = np.round(nums_parking_permits*building[:,3]/sum(building[:,3]))

# ** Calculate the vector of EV parking demand associated with each buildings**
P1 = np.round(P0*EV_Penetration)

# ** Calculate the matrix of EV of each class associated with each building**
P = np.zeros((N_B,N_C))
for b in range(N_B):
    for c in range(N_C):
        P[b,c] = P1[b]*R[c,1]
P = np.round(P)

# ** Adjust the Parking Capacity vector in order to decrease the difficulty of solving**
scale_smaller_factor = np.sum(P)/sum(q0)
q = np.round(q0*scale_smaller_factor)+2

# ** Use Cplex to Solve this model**
Set_L = range(N_L)
Set_B = range(N_B)
Set_C = range(N_C)
mip = cpx.Model(name='Cornell_Charging_Station_Network_Expanded_Model')
#Set up decision variables
I = [l for l in Set_L]
X = [(l,c) for l in Set_L for c in Set_C]
A = [(b,l,c) for b in Set_B for l in Set_L for c in Set_C]
I_vars  = mip.binary_var_dict(I, name = "I")
X_vars  = mip.integer_var_dict(X, lb = 0, name = "X")
A_vars  = mip.integer_var_dict(A, lb = 0, name = "A")
#Set up constraints
mip.add_constraints(mip.sum(X_vars[l,c] for c in Set_C)<=q[l]*I_vars[l] for l in Set_L)
mip.add_constraints(mip.sum(rho*A_vars[b,l,c] for b in Set_B for c in Set_C)<=mip.sum(X_vars[l,c] for c in Set_C) for l in Set_L)
mip.add_constraints(X_vars[l,c] <= mip.sum(A_vars[b,l,c] for b in Set_B) for l in Set_L for c in Set_C)
mip.add_constraints(mip.sum(A_vars[b,l,c] for l in Set_L) == P[b,c] for b in Set_B for c in Set_C)
mip.add_constraints(A_vars[b,l,c] == 0 for b in Set_B for l in Set_L for c in Set_C if t_indicator[b,l] == 1)
#Set up objectives
objective = mip.sum(w1*M*O*F*mip.sum((t_mean-t[b,l])*A_vars[b,l,c] for b in Set_B for c in Set_C)
                    +w2*S*O*mip.sum(R[c,2]*r*X_vars[l,c] for c in Set_C)
                   -w3*(C_S*mip.sum(X_vars[l,c] for c in Set_C)+C_G*I_vars[l]) for l in Set_L)
mip.maximize(objective)
```

```
solution = mip.solve()
N_EV = np.sum(P)
N_AEV = sum(solution.get_value(A_vars[b,l,c]) for b in Set_B for l in Set_L for c in Set_C)
N_CPL = sum(solution.get_value(I_vars[l]) for l in Set_L)
TPCfEV = sum(q)
N_CSI = sum(solution.get_value(X_vars[l,c]) for l in Set_L for c in Set_C)
MAX_CSI = max(sum(solution.get_value(X_vars[l,c]) for c in Set_C) for l in Set_L)
X_array = np.asarray([sum(solution.get_value(X_vars[l,c]) for c in Set_C) for l in Set_L])
MIN_CSI = np.min(X_array[np.nonzero(X_array)])
objective_value = solution.objective_value
construction_cost = sum(C_S*sum(solution.get_value(X_vars[l,c]) for c in
Set_C)+C_G*solution.get_value(I_vars[l]) for l in Set_L)
convenience_of_users = sum(M*O*F*(t_mean-t[b,l])*solution.get_value(A_vars[b,l,c]) for b in Set_B for l in
Set_L for c in Set_C)
Environmental_benefits = sum(S*O*R[c,2]*r*solution.get_value(X_vars[l,c]) for c in Set_C for l in Set_L)
final_value_list = [N_EV,N_AEV,N_CPL,TPCfEV,N_CSI,MAX_CSI,MIN_CSI,convenience_of_users,
Environmental_benefits, construction_cost,objective_value]
CSC_list = [sum(solution.get_value(X_vars[l,c]) for l in Set_L) for c in Set_C]

# ** Output **
path =
'Output/(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetration)+')_
(tMAX_'+str(t_MAX)+')'
if not os.path.exists(path):
   os.mkdir(path)

list_I = solution.get_values([I_vars[l] for l in Set_L])
df=pd.DataFrame(list_I)
df.to_csv(os.path.join(path,r'I___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EVR_'
+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

list_X = solution.get_values([X_vars[l,c] for l in Set_L for c in Set_C])
array_X = np.array(list_X).reshape(N_L,N_C)
df=pd.DataFrame(array_X)
df.to_csv(os.path.join(path,r'X___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EVR
_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

list_A = [sum(solution.get_value(A_vars[b,l,c]) for c in Set_C) for b in Set_B for l in Set_L]
array_A = np.array(list_A).reshape(N_B,N_L)
df=pd.DataFrame(array_A)
df.to_csv(os.path.join(path,r'A___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EVR
_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

df_P=pd.DataFrame(P)
df_P.to_csv(os.path.join(path,r'P___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EV
R_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

df_q=pd.DataFrame(q)
df_q.to_csv(os.path.join(path,r'q___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EV
R_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

df_fv=pd.DataFrame(final_value_list)
df_fv.to_csv(os.path.join(path,r'fv___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(E
VR_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

df_fv=pd.DataFrame(CSC_list)
df_fv.to_csv(os.path.join(path,r'CSC___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_
(EVR_'+str(EV_Penetration)+')_(tMAX_'+str(t_MAX)+').csv'))

# ** Visualization **
plt.figure(figsize=(20,10))
```

```
sns.heatmap(array_A,cmap="BuPu", linewidth=0.05)
plt.title('EV Assignment', fontsize=20)
plt.xlabel('Parking Lots', fontsize=15)
plt.ylabel('Selected Buildings', fontsize=15)
plt.savefig(os.path.join(path,r'Heat
map___(W1_'+str(w1)+')_(W2_'+str(w2)+')_(W3_'+str(w3)+')_(rho_'+str(rho)+')_(EVR_'+str(EV_Penetration)+')_
(tMAX_'+str(t_MAX)+').png'))
plt.show()
```